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Investigation into Stand-alone Brain-computer Interfaces for Musical Applications

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Investigation into Stand-alone Brain-computer Interfaces for Musical Applications

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RESEARCH MASTERS

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I dedicate this thesis to C.R.Viran and K.K.Rajan, my heroic granddads.

Declaration

At no time during the registration for the degree of Research Masters has the author been registered for any other University award without prior agreement of the Doctoral College Quality Sub-Committee. Work submitted for this research degree at the University of Plymouth has not formed part of any other degree either at the University of Plymouth or at another establishment.

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my friends and relatives in India, who have continued to stay in touch with me, despite me studying abroad. In my future endeavours, I hope I continue to receive love and support from all these individuals and will do my best to return the same.

Abstract

Brain-computer interfaces (BCIs) aim to establish a communication medium that is independent of muscle control. This project investigates how BCIs can be harnessed for musical applications. The impact of such systems is twofold — (i) it offers a novel mechanism of control for musicians during performance and (ii) it is beneficial for patients who are suffering from motor disabilities. Several challenges are encountered when attempting to move these technologies from laboratories to real-world scenarios. Additionally, BCIs are significantly different from conventional computer interfaces and realise low communication rates. This project considers these challenges and uses a dry and wireless electroencephalogram (EEG) headset to detect neural activity. It adopts a paradigm called steady state visually evoked potential (SSVEP) to provide the user with control. It aims to encapsulate all brain-computer music interface (BCMI)-based operations into a stand-alone application, which would improve the portability of BCMIs.

This projects addresses various engineering problems that are faced while developing a stand-alone BCMI. In order to efficiently present the visual stimulus for SSVEP, it requires *hardware-accelerated rendering*. EEG data is received from the headset through Bluetooth and thus, a dedicated *thread* is designed to receive signals. As this thesis is not using medical-grade equipment to detect EEG, signal processing techniques need to be examined to improve the signal to noise ratio (SNR) of brain waves. This projects adopts canonical correlation analysis (CCA), which is multi-variate statistical technique and explores filtering algorithms to improve communication rates of BCMIs.

Furthermore, this project delves into optimising biomedical engineering-based parameters, such as placement of the EEG headset and size of the visual stimulus. After implementing the optimisations, for a time window of 4s and 2s, the mean accuracies of the BCMI are $97.92 \pm 2.22\%$ and $88.02 \pm 9.30\%$ respectively. The obtained information transfer rate (ITR) is 36.56 ± 9.17 *bits min*$^{-1}$, which surpasses communication rates of earlier BCMIs. This thesis concludes by building a system which encompasses a novel control flow, which allows the user to play a musical instrument by gazing at it.

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Abbreviations

2D Two-dimensional

3D Three-dimensional

ALS Amyotrophic Lateral Sclerosis

API Application Programming Interface

BCI Brain-computer Interface

BCMI Brain-computer Music Interface

CBP Checkerboard Paradigm

CCA Canonical Correlation Analysis

Config. Configuration

CPU Central Processing Unit

C-VEP Code modulated Visually Evoked Potential

DFT Discrete Fourier Transform

DOF Degree of Freedom

ECoG Electrocorticography

EEG Electroencephalogram

ERD Event-related desynchronisation

ERP Event Related Potential

ERS Event-related synchronisation

FBCCA Filter Bank Canonical Correlation Analysis

FFT Fast Fourier Transform

FIR Finite Impluse Response

F-VEP Frequency modulated Visually Evoked Potential

GB Gigabyte

GLSL OpenGL Shading Language

GPU Graphical Processing Unit

ICCMR Interdisciplinary Centre for Computer Music Research

IIR infinite Impluse Response

ITR Information Transfer Rate

JFPM Joint-frequency Phase Modulation

LED Light-emitting Diode

MCN Modified Combinatorial Nomenclature

MIDI Musical Instrument Digital Interface

m-sequence Maximum Length Sequence

OpenGL Open Graphics Library

POSER Parametric Orchestral Sonification of EEG in Real-Time

PSDA Power Spectral Density Analysis

RCP Row / Column Paradigm

SCP Slow Cortical Potential

SEM Standard Error of Means

SEP Sensory Evoked Potential

SMR Sensorimotor Rhythms

SNR Signal to Noise Ratio

SSMVEP Steady State Motion Visual Evoked Potential

SSVEP Steady State Visually Evoked Potential

TTD Thought Translation Device

T-VEP Time modulated Visually Evoked Potential

TVEP Transient Visually Evoked Potential

USB Univeral Serial Bus

VEP Visually Evoked Potential

VSync Vertical Synchronisation

Chapter 1

Introduction

1.1 Motivation

It was on the 1st of February 2017, when I had first stepped into the Interdisciplinary Centre for Computer Music Research (ICCMR) lab. I was pursuing a Bachelor of Technology (B.Tech.) degree at SASTRA University, Thanjavur, India and had come to University of Plymouth, UK as a semester-exchange student. I remember feeling overwhelmed with the thought of beginning my journey in computer music, a field that elegantly combines music and engineering. I specialised in information and communication technology (ICT) during my B.Tech. degree. The field is a combination of computer science and electronics, which serves as a strong foundation for computer music. During the exchange programme, I developed my B.Tech. project under the supervision of Prof. Eduardo Miranda and Dr. Edward Braund. The project focused on contributing to ICCMR's cutting-edge research in biocomputing for music. It was a tremendous learning experience, which motivated me to pursue a master's degree in computer music. My passion for music has persisted since my childhood. It is this emotion that drives me to contribute to this vast discipline.

ICCMR carries a valuable history pertaining to interdisciplinary research at the crossroads of neuroscience and music technology (Miranda, 2014). The lab has developed musical systems by harnessing elements of affective science and brain-computer interfaces (BCIs). In addition to computer music and neuroscience, these projects encompass other disciplines — digital signal processing, computer graphics, and biomedical engineering. Therefore, research in such an area would significantly expand the technical skill-set of the researcher, which sounds tempting to an engineer. Initially, I was confused between two projects for my research master's degree — biocomputing for music or brain-computer music interfaces (BCMIs). The former is an upcoming field that encloses massive scope for creative research. I chose the latter because it is an area that I have not explored before and I was excited about the wide spectrum of technical challenges that are accompanied by it, which would enable me to learn new technologies. It would greatly test and expand my knowledge of signal processing and computer graphics and introduce me to biomedical engineering.

During my exchange-programme, I understood the significance of impact while pursuing research. In the beginning, I enjoyed computer music solely because it intensely exercised my creativity. Later on, I noticed the power of adding another dimension to the process. BCMIs aim to establish a direct communication medium between the brain and the computer. Therefore, it offers a novel mechanism of control, which is beneficial for patients suffering from locked-in syndrome. This health condition is the loss of all or most motor abilities. Initially, BCIs enabled such individuals to use wheelchairs, prosthetics, and basic communication devices like spellers (Palaniappan, 2014). Later on, this technology was extended to computer music, which enabled these patients to enrich their lives through music technology. These factors provide a strong motivation for my research project, which simultaneously allows me to delve into my cherished field and improve the lives of some individuals.

The most recent development in BCMIs within the ICCMR lab was during the PhD project by Eaton (2016), which offered the user different types of control — passive, active, and hybrid. The objective of my master's thesis is to capitalise on this highly innovative project and think of ways to improve it. I believe that neurotechnology is an extremely dynamic field. Inventions and discoveries within this domain are subject to continuous revision. This gives me the opportunity to incorporate these developments into computer music. Furthermore, there are several technical challenges that would arise while trying to perform these modifications. Considering my dual background of engineering and music, I find myself well-suited for such a project. I am inspired by the legacy of this area and strive to make an original contribution to it.

Vialatte et al. (2010) regarded BCIs as a challenging study because it involves engineering as well as biological aspects. Over the years, there has been greater attention drawn towards interdisciplinary research. The act of merging 2 different domains allows them to contribute to each other, which leads to momentous progress and development in both. I am enthusiastic about being introduced to biomedical engineering. It would help understand the underlying behaviour of the nervous system. In the future, I am interested to explore affective science, psychology, and physiology with respect to music and this project would be a significant stepping stone towards achieving my long-term goal. I would like to begin my thesis by quoting an equation from Chatterjee (2012), a book that is inspired by the *Bhagavad Gita*.

$$Evolution = Discipline + Freedom$$

1.2 Research Questions

This project conducts research at the intersection of three different disciplines — neuroscience, biomedical engineering, and music technology. Neuroscience comprises physical, functional, and morphological studies of the central nervous system (Shulman, 2013). It helps us understand the underlying aspects of brain waves. In this thesis, biomedical engineering expounds how information can be obtained from the brain through methods like electroencephalography (EEG). The eventual outcome of the project is to build an application that allows the user to control a musical interface. Conventionally, in order to play a musical instrument, we require muscular power in some form or the other. For example, we play the piano with our hands and control its pedals by using our feet. As mentioned earlier, BCIs aim to directly interface the brain with a computer. Therefore, this project aims to develop a musical system that is independent of, or demands minimum muscular control.

Detection of neural activity requires sophisticated sensors, which are often confined to the boundaries of laboratories. This project aims to adopt methods of detection that support portability. In comparison to conventional computer interfaces, BCIs face several limitations. They realise considerably lower communication rates. In terms of patterns observed in brain waves, there is notable scope for new discoveries. These newly observed phenomena can be incorporated in order to improve communication between the user and the BCMI. They would provide better information regarding what the user wants to convey to the BCMI. Thus, the objectives of this project are condensed into two research questions as follows.

RQ1 *How can we make BCMI technologies more usable for practical deployment in real-world scenarios?*
There are several laboratories all over the world that specifically conduct research in BCIs. With the passage of time, developments within this field have demonstrated its potential as a communication medium. Within the BCI community, there is rigorous research being conducted to unfold this technology from laboratories to real-world scenarios. Invasive and non-invasive methods are two ways of detecting brain waves. The invasive method, as the name suggests implants electrodes directly into the head. This is suitable for clinical diagnosis, but not for regular use in BCIs because it is prone to problems such as infection. Non-invasive sensors have grown in popularity due to their convenience. However, this advantage is accompanied by a loss of signal quality, which hinders the performance of BCIs. Although non-invasive sensors improve portability when compared to invasive ones, it does not mean that they can be easily adopted in real-world situations. There are various other factors like set-up time and the use of substances like gel to improve signal quality.

This thesis aims to address these challenges to make BCMIs more usable for real-world applications.

This project also examines the platforms used to deploy BCMIs. Within the world's technological sphere, most individuals expect a smart-phone, tablet, or a computer version of every application. BCI systems generally use bespoke hardware to accurately render operations. This project explores the prospects of deploying BCMIs in commercial platforms such as the three mentioned above. It aims to exploit their ubiquity to increase the outreach of neuroscience. However, this objective comes along with many technical challenges because these platforms are not real-time operating systems (Cecotti et al., 2010). Therefore, many considerations need to be taken into account in order to achieve this goal.

RQ2 *How can we improve the communication rates of BCMI systems?*
As mentioned earlier, BCMIs are significantly different from conventional interfaces. For example, in order to adjust volume in a conventional musical interface, you would simply turn a knob until it produces the desired output. However, performing the same function in a BCI is more complicated. Sophisticated interface objects like knobs have not been implemented. Instead, we are at a stage where we can choose from an array of binary buttons on the interface! Hence, the speed at which the user can convey information is a key problem faced by these systems.

Non-invasive methods of detecting neural activity lead to a compromise in signal quality. As this project aims to improve the portability of BCMIs, it is crucial to consider its effect on the system's performance. The output produced by the BCMI is a function of the subject's brain waves. Thus, poor signal quality leads to incorrect information detected by the system. Hence, accuracy is an important issue tackled by BCI researchers. Developments in neuroscience have found ways of improving signal-to-noise ratio (SNR) of brain waves. Techniques such as filtering, statistical signal processing, optimal positioning of sensors, detection from multiple regions of the head, and so on have proven to make these systems more robust. Therefore, this project aims to incorporate these principles into BCMIs that use portable sensors, which would be a novel contribution to this interdisciplinary field.

1.3 Research Methodology

This section presents an overview of the research methodologies adopted by the project. It discusses about methods used to detect brain waves, programming language to develop the BCMI, and research tools to analyse neural activity.

1.3.1 Wireless and dry EEG Headsets

Broadly, there are two ways of performing non-invasive EEG — wet and dry. The former uses gel to improve the contact between the scalp and the sensor. This is the most popular method of detection in BCI experiments because it provides reasonable signal quality. The latter is more convenient and requires less set-up time, but suffers from poorer signal quality. A more detailed explanation on wet and dry EEG is given in section 3.2. This thesis adopts dry EEG as the method for detecting neural activity, which is the first step taken towards answering RQ1. In order to obtain reliable performance, most BCMI systems in the past have adopted medical-grade EEG headsets (Eaton, 2016). These are bulky, comprise wiring, etc., which make them less usable. Earlier projects in ICCMR have attempted to use portable headsets, but realised poor communication rates. This thesis adopts a customised EEG headset manufactured by Cognionics, Inc., which is dry and wireless. All experiments conducted within this project are restricted to using this hardware framework in order to realise bespoke optimisations. Over the years, there have been several developments in BCI paradigms, such as improvements in signal processing techniques, which can be incorporated into BCMI systems. Therefore, this would provide a more rigorous evaluation on the feasibility of using wireless and dry systems for BCIs. As BCMIs are bound to be deployed in scenarios like musical performances, it is advantageous to have a wireless and dry EEG sensor.

1.3.2 Cross-platform Development

In order to build a stronger foundation to answer RQ1, this project examines the platforms used to deploy BCMIs. As sub-operations carried out by BCMIs are computationally expensive, researchers have used separate processors to perform them independently (Wang et al., 2011). Due to the complex nature of these functions, they are normally implemented in high-level programming languages like Python and MATLAB. These systems provide an excellent framework for data analysis and to understand the underlying principles of brain waves, but are computationally less efficient. Furthermore, they impose restrictions while deploying on alternative platforms like tablets and mobile-phones. Hence, this thesis explores the development of a stand-alone BCMI by using a lower-level programming language like C++. This demands the implementation of a programme to receive data from the EEG headset, signal processing algorithms that encompass complex mathematical operations, and functionality for music such as audio output. Furthermore, BCMIs that are based on visual stimuli require instructions to be passed directly to the graphical processing unit (GPU), in order to exploit the complete computational potential of the hardware framework. The above operations need to be encapsulated into one module that is independent of external processors and applications.

1.3.3 EEG Analysis

Adolf Beck, one of the early pioneers in EEG observed two-pattern rhythmic activity in brain waves of dogs (Coenen et al., 2014). Subsequently, Hans Berger discovered alpha rhythms in the 1920s and coined the term electroencephalogram (Millett, 2001). Since then, there has been attention drawn towards the frequency-based characteristics of brain waves, commonly referred to as EEG rhythms. Many signal processing principles overlap in neuroscience and computer music. In order to analyse frequency-domain features, power spectral density-based analysis (PSDA) has been a popularly used method in both domains. As mentioned earlier, non-invasive detection provides lower signal quality. Therefore, researchers have explored the prospects of multi-channel EEG, where signals are detected from multiple regions of the head. Alongside this change in method of detection, there needs to be modifications in signal processing techniques to analyse the data. Scientists have proposed statistical signal processing that adopts multivariate analysis instead of PSDA (which is univariate) (Lin et al., 2007). This thesis aims to incorporate these developments into BCMI systems and thus, which would focus on answering RQ2. However, it is important to note that all these sophisticated procedures need to be implemented in a lower-level programming language (this project uses C++). Hence, certain considerations need to be made while designing algorithms. Additional factors like filtering EEG data and optimal sensor location, to name but two, have proven to improve the communication rates of BCIs (Chen et al., 2015a; Wang et al., 2006). This project explores these parameters to improve communication rates of BCMI systems. MATLAB has been used to conduct an offline analysis of EEG in order to design an optimal algorithm. Later on, these procedures are implemented in C++.

1.4 Thesis Structure

Including the current chapter, this thesis consists of 5 chapters. The subsequent chapters are described in the following.

Chapter 2: This chapter conducts a survey on different types of BCMI systems — passive, motor imagery, P300, and steady state visually evoked potential (SSVEP). The framework used to compare these systems is based on the two research questions of the project. The first criterion within the framework evaluates the usability of the BCMI, which emphasises on RQ1. The second criterion analyses the communication between the user and system, which addresses RQ2. After an in-depth qualitative and quantitative analysis, the chapter chooses SSVEP as the optimal paradigm, which is investigated in the remainder of the thesis. Furthermore, the chapter explores how EEG can be harnessed to build a portable system and examines trends in neurotechnology to strengthen the communication between the user and system.

Chapter 3: There are 4 sub-operations that are carried out by SSVEP-based BCMIs — providing the visual stimulus, detect EEG, analyse EEG, and output. In this chapter, a system is designed to harness SSVEP for active control and 2 of the above sub-operations are implemented within the C++ framework. Thus, it partially answers RQ1. It delves into the technical aspects involved in exploiting the GPU for hardware-accelerated rendering and the development of an additional *thread* to receive data from the EEG headset. In recent years, there have been developments in mathematical functions that define the visual stimulus, which have been integrated into this system. Experiments are conducted on 8 different subjects to test the reliability of the headset for SSVEP. An offline analysis of the EEG data is conducted in MATLAB. The chapter designs a novel filter and incorporates statistical signal processing to improve communication rates of the system. Considering the fact that it adopts dry and wireless EEG, it realises high values of speed and accuracy.

Chapter 4: After developing a BCMI system in chapter 3, which partially answers both research questions, this chapter explores different parameters of optimisation to improve communication rates. The BCI literature is sparse with regards optimising systems for portable and dry EEG headsets. After applying these optimisations, there was a significant increase in the speed and accuracy of the BCMI. Therefore, this chapter provides a notable contribution to answering RQ2. Furthermore, the remaining 2 sub-operations are implemented within the C++ framework. All the 4 operations are encapsulated into one stand-alone application and thus, completely answering RQ1. Finally, a BCMI system with a bespoke control is developed. The user is allowed to control a musical interface solely by gazing at different regions.

Chapter 5: This chapter concludes the thesis. It summarises how the research process has provided answers to both research questions. Additionally, other conclusions that are not directly answering the research questions have been discussed. The chapter also presents a foundation for future work. It provides an in sight into the pathways for future research in BCMI systems.

Chapter 2

Music Technology Crossing Paths with Neuroscience and Biomedical Engineering

2.1 Overview

Brain-computer interfaces (BCIs) aim to establish a direct medium of communication between the brain and the system, which is independent of muscular control. Such an interface is advantageous to patients who are suffering from motor disabilities and individuals who want to delve into this novel pathway of control. This chapter presents a survey on 4 categories of BCIs for music technology — passive, motor imagery, P300, and steady state visually evoked potential (SSVEP). Based on the challenges faced by neuroscience and biomedical engineering, it compares these paradigms based on two criteria — (i) usability of the brain-computer music interface (BCMIs) and (ii) communication between the user and system. It primarily focuses on BCIs based on electroencephalogram (EEG), which is a non-invasive method to detect brain waves. The framework investigates important issues prevalent in BCI research, such as method of detection, user-centric and environmental conditions, speed, and accuracy, to name but few. Each technique has exclusive advantages over the other and hence, an in-depth analysis into choosing an appropriate technique is conducted. The chapter concludes by reviewing the most appropriate category of BCIs for musical interfaces and examines the prospects of harnessing it to develop portable and robust BCMI systems.

2.2 Introduction

Research in the field of neuroscience and biomedical engineering has persistently re-evaluated the need for muscular control to express oneself. Electroencephalography, which is a method of recording neural activity has contributed to several external disciplines — building emotional models in affective science (Kumar and Kumar, 2015), studying dreams and sleep in oneirology (Rome, 1981), diagnosing epilepsy in neurology (Smith, 2005), and developing control systems in BCIs (Ramadan and Vasilakos, 2017), to name but few. These studies aim to establish a direct medium of communication between the brain and the external environment. Therefore, it opens up opportunities to create systems that are based on electroencephalogram (EEG) data. For example, Stikic et al. (2014) built an EEG-based classifier for positive and negative emotional responses of users to comedy and tragedy-based video clips. Such a system employs neural activity to obtain feedback from the user instead of relying on a manually-entered description.

By developing BCIs, biomedical engineering has explored the prospects of providing control to the user. Primarily, they can be classified into 2 categories — *active* and *passive* control. On one hand, active control is the process of allowing the user to make discrete choices. For instance, in the field of intelligent transportation, Fan et al. (2015) proposed a vehicle-driver interface that allowed the user to select the destination of travel. On the other hand, passive BCIs enable the user to indirectly influence the output of the system. Blankertz et al. (2010) proposed a BCI that measured the mental workload of a user, which is used to evaluate products (lower the workload means better the product) for safety purposes (George and Lécuyer, 2014).

As BCIs aim to achieve a communication medium that is independent of muscle control, they are beneficial for patients who are suffering from locked-in syndrome, which is the loss of all or most motor abilities. Locked-in syndrome can be caused due to diseases like stroke, spinal cord injury, or amyotrophic lateral sclerosis (ALS). Initially, active control advocated the development of BCI-based wheelchairs, prosthetic limbs, and basic communication tools such as spellers (Palaniappan, 2014; Rezeika et al., 2018). Over the years, the applications of BCI have been extended to controlling mouse cursors (McFarland et al., 2008), virtual reality (Lécuyer et al., 2008), music technology (Miranda and Brouse, 2005), environmental control (turn on/off lights) (Gao et al., 2003), and so on. Such technologies are not only helpful for patients, but provide alternative mechanisms for healthy individuals to operate systems.

Computer music has been incorporating methodologies from neuroscience to develop BCMI systems (Miranda and Brouse, 2005). A classic example of the early works in this interdisciplinary field is Alvin Lucier's *Music for a Solo Performer* in 1965, which was based on the sonification of EEG (Lucier, 1976). This inspired several computer musicians to explore this novel dimension of control. Teitelbaum (1976) controlled parameters of electronic sound synthesisers and opened up pathways for biofeedback music, which focused on harnessing passive control for composition. Hinterberger et al. (2004) implemented a thought-translation device (TTD), which enabled the user to give auditory feedback. Hinterberger and Baier (2005) presented parametric orchestral sonification of EEG in real time (POSER), in which multiple frequency bands are mapped to different instruments of a musical instrument digital interface (MIDI) device. Grierson (2008) explored the prospects of active control for musical instruments. Grierson and Kiefer (2014) extended its application to creating a scale player and algorithmic improviser.

Progressive developments in BCI technologies have expanded the spectrum of music technology applications. However, there are several challenges that are faced while adopting a BCI. In order to achieve good signal to noise ratio (SNR) of EEG, it requires the use of sophisticated EEG headsets. Such headsets are appropriate for medical scenarios and clinical use, but impose hindrances in terms of portability, wiring, ease of use, and set-up time. Considering the nature of musical performances, it reduces the flexibility for musicians to incorporate such technologies in their practices. Scientists have focused on improving the usability of these headsets. However, this is accompanied by a compromise on the quality of EEG signals (Hairston et al., 2014). Another crucial problem faced by the BCI community is the communication rates of these systems. Communication rate, as the name suggests, refers to the rate at which the user can convey information. The design of conventional musical interfaces are considerably different from BCMIs. The former generally comprises knobs, faders, keys, and triggers, to name but few. For BCMIs, this level of sophistication in interface-design is impractical. This project aims to improve the usability of BCMIs in practical scenarios. It also aspires to increase communication rates of existing systems. Therefore, this chapter studies the different types of BCIs that have been tailored for musical systems. It evaluates each system based on two criteria — (i) usability of the BCMI and (ii) communication between user and system. An explanation of these criteria is given in the following section. Four different BCI paradigms — passive, motor imagery, P300, and steady state visually evoked potential (SSVEP) are evaluated for musical applications. The literature is sparse with regards to harnessing motor imagery for musical control. However, the other three techniques have been widely explored by computer musicians. It is also important to note that this list of 4 paradigms is not exhaustive. For instance, techniques like using EEG signatures of emotion have not been analysed in this chapter. The survey has been limited to these 4 paradigms because they seem to be the most popular ones. This chapter is directed towards choosing an appropriate BCI for musical applications and reviews some technical specifications of the chosen paradigm.

2.3 Criteria of Comparison

This section expounds the framework adopted by the survey to compare different BCMI systems. It also aims to delineate the link between the framework and research questions of the project.

2.3.1 Usability of the BCMI

Firstly, this criterion considers the method that is adopted to detect brain waves. It can be categorised into invasive and non-invasive. The former is to implant electrodes (conductive devices to detect electrical activity) directly into the brain. It provides very high quality of signals (Anupama et al., 2012). The latter records EEG waves through devices that are mounted on the subject's head. It provides poorer signal quality, but is more convenient, safer, and has less chances of infection (Palaniappan, 2014). Different BCI systems detect EEG signals from different regions of the head. Therefore, the sophistication of designing the headset is analysed. Secondly, this criterion assesses the environmental conditions that are imposed by the system. For example, BCIs based on gaze-control may not perform well in bright environments. External light might be an unavoidable artefact during live musical performance and therefore, this is a crucial factor while deploying BCMIs in real-world scenarios. Thirdly, it observes the conditions imposed on the user while using the system. For instance, some BCIs require user-training, which might not be suitable for all subjects.

2.3.2 Communication Between User and System

The output of a BCMI can be visualised as a function of neural oscillations observed in the user. As passive BCMIs encompass an indirect association with the output, it is often difficult to make differences noticeable to the user. Hence, sufficient control over the BCMI might not be realised. This issue is negligible in active BCIs and therefore, accuracy becomes a crucial factor. Accuracy in one of the key problems that have been tackled by neuroscientists. Over the years, several signal processing techniques have been proposed to improve the SNR of EEG (Lin et al., 2007; Rezeika et al., 2018; Wang et al., 2006). However, a trade-off between speed and accuracy is common in BCIs (Chen et al., 2014). When the time taken to detect the user's response is increased, the accuracy simultaneously improves. A common metric called information transfer rate (ITR) is adopted to quantify the two parameters. A detailed explanation on ITR is given in section 3.6.

Furthermore, this criterion studies the relationship between the activity performed and the actual application. As mentioned earlier, BCMIs are notably different from conventional interfaces. For example, consider a pianist who is comfortable with playing a piano with weighted keys. This comfort might be slightly reduced while using a keyboard with light keys. It will be further reduced while playing a virtual keyboard on a computer-screen with a mouse. Moreover, the significance of this factor maybe magnified when considering the case of patients with motor disabilities. They might visualise the BCMI as a substitute for their hands while using a musical interface. Therefore, this relationship between the activity and application plays an important role in evaluating the communication between the user and the BCMI.

2.4 BCMI Systems

2.4.1 Passive

Interdisciplinary research at the crossroads of computer music and another field often spawns from an experiment of sonification. Early BCMI systems were governed by this principle (Lucier, 1976; Rosenboom, 1990; Teitelbaum, 1976). Sonification is the process of mapping data to sound. It can be used for a variety of purposes. In medicine, Baier et al. (2007) translated EEG rhythms of well-known epileptic disorders into sound samples for online monitoring. Hermann et al. (2002) proposed techniques to sonify EEG data obtained from psycholinguistic experiments. BCMIs for sonification have also adopted slow cortical potentials (SCPs) to serve as input data (Hinterberger and Baier, 2005). They detect increased and decreased neuronal activities, which are attributed to negative and positive SCPs respectively (Birbaumer et al., 1990; Nicolas-Alonso and Gomez-Gil, 2012). The user's physiological data serves as binary control signals for the system (Palaniappan, 2014).

Passive BCMIs normally use non-invasive techniques to record EEG. Spectral analysis of EEG commonly serves as input data. Audification, which can be considered as a special case of sonification (Hermann, 2008) is the direct translation of neural oscillations into audio frequencies. Range of frequencies observed in brain waves is very different from audio signals. These BCMIs normally consider neural frequencies in the range of 0.1Hz to 35Hz (Hermann et al., 2002; Straebel and Thoben, 2014). Hence, they are useful to identify pitches and rhythms in EEG. Musification is the translation of brain waves into musical parameters or higher-level structures such phrases, melodies, songs, and so on. Computer musicians have avidly used this technique to achieve passive control for composition and live performance (Miranda and Brouse, 2005; Rosenboom, 1990). Conditions imposed on the environment and the user in passive BCMIs are minimal. They tend to focus more on mapping procedures as opposed to obtaining high-quality signals. Therefore, their usability is high. However, if the system is based on SCP, user-training is required. Factors like psychological state, motivation, and physical well-being of the user need to be considered. Furthermore, the relationship between the user and the trainer plays a crucial role (Hinterberger et al., 2003; Nicolas-Alonso and Gomez-Gil, 2012).

Walker and Nees (2011) stated that sonification aims to exploit human auditory perception to make data relationships comprehensible. Frequency ranges of brain waves and audio signals are greatly different. Neural activity is measured in microvolts and hence, it must be amplified by a large factor (Rowan and Tolunsky, 2003). Transposition within the frequency domain and the amplification of signals act as potential sources of noise. Hinterberger and Baier (2005) developed (POSER), which extracted parameters from EEG and mapped it to a MIDI device. It was based on the thought translation device (TTD) created by Hinterberger et al. (2003), which used SCP. Generally, the technique has been adopted by BCMIs for passive instead of active control due to low communication rates. Miranda and Brouse (2005) devised a BCMI-piano that aimed to predict what might be going on inside the subject's mind. It assumed the association between mental activities and physiological information (Petsche, 1990). However, establishing a distinct rationale behind the output to the user is a challenge faced by these systems. Alternatively, biofeedback has been investigated to improve the user-participation (Miranda et al., 2003; Rosenboom, 1977; Teitelbaum, 1976). *MoodMixer* developed by Leslie and Mullen (2011) incorporated elements of affective science in BCMIs. In this installation, different sound tracks corresponded to different mental states of the user and therefore, there existed a stronger relation between the activity being performed and the application. A similar relation can also be observed while using SCPs. High and low energy sound tracks can be associated to negative and positive SCPs respectively. However, solely relying on these attributes limits our choice set and is a relatively slow process. Hence, subsequent sections analyse BCMI systems that harness active control.

2.4.2 Motor Imagery

Motor imagery, as the name suggests, realises active control by allowing the user to imagine a specific motor activity. It aims to consciously access a motor representation, which is generally a non-conscious mechanism (Jeannerod, 1995). For instance, the subject visualises a movement of the left or right hand, which corresponds to a particular function (Pfurtscheller and Neuper, 1997). These BCIs are based on a specific type of neural activity called sensorimotor rhythms (SMRs), which are detected over the sensorimotor cortex of the brain (Yuan and He, 2014). SMRs produce two types of amplitude modulations — event-related synchronisation (ERS) and event-related desynchronisation (ERD), which are analysed to calculate the user's response.

Invasive as well as non-invasive methods have been used for motor imagery. Felton et al. (2007) harnessed electrocorticography (ECoG) to control a computer interface. Anupama et al. (2012) described ECoG as a partially invasive technique because electrodes are placed inside the skull, but outside the grey matter of the brain. Studies have regarded ECoG as a balance between signal quality and invasiveness (Huggins et al., 2003). However, EEG has prevailed in the literature for motor imagery. Electrodes are normally placed in the central and parietal region[1] of the head, which enclose the motor cortex (Kübler et al., 2005; Pfurtscheller et al., 2006; Pfurtscheller and Neuper, 2001). External conditions or stimuli like light and sound do not directly affect the performance of the system because the output is a consequence of the user's imagination. However, these conditions might serve as distractions to the subject. User-training is an important process in motor imagery. Scientists have persistently worked towards delineating the physiology of the technique (Beisteiner et al., 1995). Users get confused between mental images and actual movements (Nicolas-Alonso and Gomez-Gil, 2012). Neuper et al. (2005) demonstrated the importance of kinesthetic aspects as opposed to visual imagination of actions during user-training. Frølich et al. (2015) investigated the types of artefacts in motor imagery. Muscular movement was identified as the most prominent interference with EEG. Furthermore, electrooculographic activity such as eye movements and blinks also act as potential impediments to these systems (McFarland et al., 1997, 2005). Therefore, users should aim to minimise these artefacts while using motor imagery-based BCIs.

Pfurtscheller and Neuper (2001) created a binary classifier (or two-class system) with an accuracy of nearly 100%. Blankertz et al. (2008) tested a BCI on novices without user-training and realised an accuracy of greater than 84% for the majority of subjects. Studies have focused on increasing the number of control signals for motor imagery, which is usually accompanied by a decrease in classification-accuracy. Taylor et al. (2002) developed and tested neuroprosthetic devices for humans and monkeys. The study scanned cortical neurons through invasive electrodes and allowed the user to control an artificial limb within a three-dimensional (3D) space. This demonstrated multi-dimensional control in BCIs through motor imagery. The advantage of multi-dimensional communication is that it enables the user to control multiple parameters like pitch and rhythm simultaneously. Alternatively, by using non-invasive EEG, Wolpaw and McFarland (2004) achieved two-dimensional (2D) movement of a mouse cursor. In order to evaluate communication in BCIs, Yuan and He (2014) considered a parameter called degree of freedom (DOF), which was the number of independent control signals derived from neural activity. Miller et al. (2007) realised

[1]Refer to Luck (2014); Oostenveld and Praamstra (2001); Rowan and Tolunsky (2003) for more information about placement of scalp electrodes

high DOF by examining sets of five movement modalities, for example — shoulder, foot, hip, hand, and tongue. Schalk et al. (2008) incorporated these modalities and achieved a success rate of $53-73\%$. Djemal et al. (2016) presented a three-class system with an accuracy of $86-93\%$ and an ITR of up to 21 *bits min*$^{-1}$, which is a high value for motor imagery. Considering the current limitations of BCIs, motor imagery offers high relation to the actual activity being performed. Examples of motor imagery tasks such as movement of limbs can be related to rhythmic actions. This is an interesting aspect to explore for musical applications.

2.4.3 P300

P300 falls under a class of BCIs that are based on event-related potentials (ERPs). ERP is an electrical potential observed in EEG as a response to specific events or stimuli. It can be elicited by sensory, cognitive, and motor[2] events (Blackwood and Muir, 1990; Luck, 2014). P300 (also known as P3) is a contraction of the terms 'positive' and '300 milliseconds'. The P3 wave is a positive deflection that occurs approximately 300 milliseconds after the onset of an event. Essentially, it is based on the *odd-ball* paradigm, which presents an infrequent target alongside a frequent stimulus. Auditory, visual, and somatosensory stimuli are common ways to realise the paradigm. For instance, if the probability of two discrete sounds at 1000Hz and 500Hz is 0.8 and 0.2 respectively, the user discriminates the infrequent sound by exhibiting a P300 response on its occurrence (Polich, 2012). The technique has been adopted to build musical interfaces that offer active control. Grierson and Kiefer (2014) discussed the development of a P300 scale player, composer, and algorithmic improviser. The P3 wave has also lead to other interesting studies like George and Coch (2011), which investigated the working memory in musicians and non-musicians during musical training.

As P300 adopts EEG, it uses non-invasive headsets to detect brain waves. The literature does not provide a unanimous interpretation about the neural and cognitive processes behind the P3 wave (Luck, 2014). Barrett et al. (1987); Naumann et al. (1992) discovered that the scalp topography of the wave differed from one stimulus modality to the other (visual, auditory, or touch). However, Picton (1992) suggested that P3 measurements are typically taken from the Cz or Pz location, but a greater electrode density provides higher accuracy. Environmental conditions of the BCI depend on the type of stimulus being used. An auditory stimulus might not be appropriate for musical systems because of interference from the output, that is the user will have to be isolated from the performance. Kaufmann et al. (2013) demonstrated that P300 systems based on tactility were more accurate than vision or sound

[2] In this context, ERP is a response to motor activity, which is different from motor imagery

for up to 4 choices. Musical interfaces generally require a greater degree of flexibility. In this context, a visual-based system is more appropriate because it allows greater number of options. For instance, Nijboer et al. (2008) presented a 49-choice speller that was tested on ALS patients. A bright environment is not be suitable for visual-based P300 because it will interfere with the stimulus. While using the system, the subject is expected to gaze at the target choice. In addition to muscle noise and cardiac signals, eye artefacts are a significant impediment in P300 research (Jung et al., 2000). Therefore, the user is expected to avoid blinks and saccades while using the system.

As mentioned earlier, the number of choices available through visual-based P300 systems is fairly high. A matrix grid like 6×6 or 7×7 is a popular design for such BCIs. For several years, the row/column paradigm (RCP) proposed by Farwell and Donchin (1988) was widely adopted to grant the user active control. Townsend et al. (2010) proposed a novel stimulation technique called the checkerboard paradigm (CBP) and compared the two techniques. CBP and RCP achieved an ITR of 23 $bits\ min^{-1}$ and 17 $bits\ min^{-1}$ respectively. The experiment also presented a 8×9 grid, which corresponded to 72 choices. Besides spelling, P300 has been adopted in several applications like brain painting, virtual reality, and gaming (Fazel-Rezai et al., 2012). There are notable differences between using a musical instrument through gaze-control and other conventional means. The technique serves as a novel paradigm for communicating with the interface, but restrictions in muscular movement and fixing the user's vision to the interface during musical performance might be disengaging (Eaton, 2016). Furthermore, this technique permits only unidimensional communication. Hence, the user will not be able to control multiple aspects like pitch and rhythm simultaneously. However, features like visual and audio feedback to denote the choice made by the user improves user-participation. As these systems are often developed by using general purpose computers, graphical objects and animations may serve as a compensation.

2.4.4 SSVEP

Steady state visually evoked potential (SSVEP) belongs to a category called sensory evoked potentials (SEPs). SEPs are created when nervous tissues respond to a stimulation such as clicks, electrical pulses, and flashes for auditory, somatosensory, and visual stimuli respectively (Misulis and Head, 2003). Unlike ERPs, SEPs are locked in phase with the stimulus, which can be enhanced through signal averaging and performing multiple trials (Başar, 1980; Başar et al., 1999; Vialatte et al., 2010). SEPs that are evoked by using visual stimuli are coined as visually evoked potentials (VEPs). One of the early VEP-based BCIs was developed by Sutter (1992), which adopted transient VEP (TVEP). TVEPs are obtained at low stimulus rates where average responses are locked in time with the triggering stimulus (Regan, 1989; Tobimatsu, 2002). While TVEP interprets time-domain characteristics, SSVEP occurs at higher rates and exploits frequency-domain features. The user is provided with active control by presenting multiple regions flashing at unique frequencies. The corresponding frequency is induced in EEG, which can be detected through spectral analysis. Miranda et al. (2011) adopted SSVEP to enable the user to make choices from an array of musical notes.

SSVEP-based systems have predominantly used non-invasive electrodes. The signal strength of SSVEP is highest in the occipital region, which encloses the visual cortex (Wang et al., 2010). Some studies have also realised high SNRs in the parieto-occipital region (Chen et al., 2015b). Wang et al. (2008) stated that these BCIs could either use 2 electrodes (O1 and O2 location) or higher densities of 4 to 12 electrodes. Evidently, they follow the pattern of more electrodes leading to more reliable signals. Vialatte et al. (2010) reported that the size of and distance from the stimulus might affect the performance of SSVEP. Bright and noisy environments are potential causes for decrease in communication rates (Wang et al., 2006). The user is required to avoid eye blinks and muscular movements. Using the system over prolonged duration leads to mental load and visual fatigue, which causes a decrease in SSVEP amplitude (Xie et al., 2016). While using the system, subjects might be unable to adapt to the flashing lights and have to sit in a fixed posture, which causes physical discomfort (Hasan et al., 2013). The above factors account for imperative restrictions imposed on the user and environment while adopting this technique.

There has been a perpetual growth in communication rates for SSVEP. In the first international meeting devoted to the BCI research, systems realised ITRs between 5 – 25 *bits min*$^{-1}$ (Wolpaw et al., 2000). Over the years, there have been several improvements in mathematical functions that define visual stimuli and signal processing techniques to analyse EEG. The method has been widely adopted for applications in computer games (Lalor et al., 2005), robotics (Bell et al., 2008), and three-dimensional (3D) navigation (Wang et al., 2018), to name but few. Chen et al. (2015b) achieved an ITR of 319.2 *bits min*$^{-1}$, which is the highest recorded communication rate for both invasive and non-invasive BCIs. The system presented a 40-target speller which allowed the user to enter one character per second. SSVEP suffers from a thin relation between the application and the actual activity being performed. Similar to P300, SSVEP is method of unidimensional communication. However, visual feedback through graphical animations can be incorporated to improve user-engagement in the system.

2.5 Comparison of BCMIs

This section presents an in-depth discussion on the 4 types of BCMI systems based on the proposed framework of comparison. All categories recognise EEG as a feasible and optimal way of detecting brain waves. This makes them convenient because it is a non-invasive technique. Topography of electrode placement is specific to the type of system and BCIs improve performance by increasing electrode density. However, the cost of manufacturing EEG headsets generally depends on the number of electrodes and not their orientation. Passive systems and motor imagery do not require specific environmental conditions because they are endogenous in nature. P300 and SSVEP need to be placed in environments that are dimly or moderately lit because they are based on visual stimuli. This might hinder the deployment in live musical scenarios. Considering subject-centric conditions, motor imagery inevitably requires training. If the passive BCMI adopts SCP, user-training is necessary. Training sessions for motor imagery span from few days and weeks to even months (Birbaumer et al., 2003; Mulder, 2007; Pascual-Leone et al., 1995; Wolpaw and McFarland, 2004). User-training improves performance in SSVEP and P300, but it is not essential. Moreover, optimisations in signal processing techniques have been proposed to achieve high communication rates through unsupervised classification algorithms (Islam et al., 2017; Nakanishi et al., 2014a). The visual-based systems induce visual fatigue and tiredness, which reduce their usability over prolonged durations. Table 2.1 summarises the above points based on the three parameters — convenience of detection, environmental conditions, and user-centric conditions.

BCMI	Method of Detection	Environmental conditions	User-centric conditions
Passive	Good	Good	Good
Motor Imagery	Good	Good	Satisfactory
P300	Good	Satisfactory	Satisfactory
SSVEP	Good	Satisfactory	Satisfactory

Table 2.1 Comparison of BCMIs based on method of detection, environmental conditions, and user-centric conditions.

There is a remarkable difference of ITRs observed in SSVEP when compared to the rest of the paradigms. Taking note of the above discussions, SSVEP-based systems can be up to 10 times faster than other BCIs. Vialatte et al. (2010) argued that the performance of SSVEP highly depends on experimental design. Minor differences in unnoticed or uncontrolled parameters lead to variations in performance. However, several laboratories report ITRs between $130 - 170$ $bits\ min^{-1}$ (Chen et al., 2015a; Erkan and Akbaba, 2018; Nakanishi et al., 2014b), which is at least 5 times higher than other techniques. ITR is an amalgamation of accuracy, number of available choice, and speed of detection. If you observe, the ITR in P300 and motor imagery is almost equal. The former offers a huge number of choices to the user. It is commonly higher than SSVEP as well. The latter provides up to 5 choices, but 3 with reliable accuracy. The speed of detection is higher in motor imagery when compared to P300 and thus, they have similar ITRs. Having only 3 different choices can impose limitations for a musical interface. A passive system struggles to delineate a clear relation between the user's response and the output. P300 and SSVEP are visual-based systems that operate based on the user's gaze-control. The subject will have to avoid eye blinks and minimise muscular movements, which might prevent them engaging with the music. However, visual and auditory feedback may compensate for this issue. Motor imagery has the minor advantage of it being endogenous and thus, does not depend on the external environment. Table 2.2 depicts the comparison of BCMIs based on communication.

BCMI	**Communication rate**	**Relation**
Passive	Low	Low
Motor Imagery	Medium	High
P300	Medium	Medium
SSVEP	Very high	Medium

Table 2.2 Comparison of BCMIs based on communication. *Relation* in table stands for relation between the activity and the actual application.

Figure 2.1 illustrates an evaluation of all 4 BCMIs based on usability of the BCMI and communication between the user and system. Both motor imagery and SSVEP serve as potential paradigms for BCMIs. The former strikes a reasonable balance between the two criteria and the latter realises very high ITR. Let us consider few examples of musical interfaces in order to conduct a deeper analysis. Piano serves as a popular test case for computer music studies. In order to cover all the notes within an octave, it requires 13 choices. This is achievable through SSVEP, but not motor imagery. Moreover, SSVEP would facilitate the expansion to multiple octaves. Contrarily, the sound of percussion instruments like Drum kit, Tabla, Taiko, Tambourine, etc. can be condensed and approximated to few choices of 2 to 4 and still maintain their characteristic sounds. As mentioned earlier, motor movements can be associated to percussion-like activity and therefore, motor imagery is more suitable for such an application. Let us take examples of musical tools that are not for performance. In order to develop a BCI-based software that allows a user to create a composition, it would be convenient to have different options for pitch, loudness, duration, and rhythm. In order to achieve this through motor imagery, the user will have to navigate between huge number of screens with binary choices, which would be time-consuming. Making musical selections like arpeggios, melodies, and songs would require high degree of flexibility during interface design. Hence, based on current trends in BCI technologies, this chapter concludes SSVEP as the most suitable technique to develop BCMI applications.

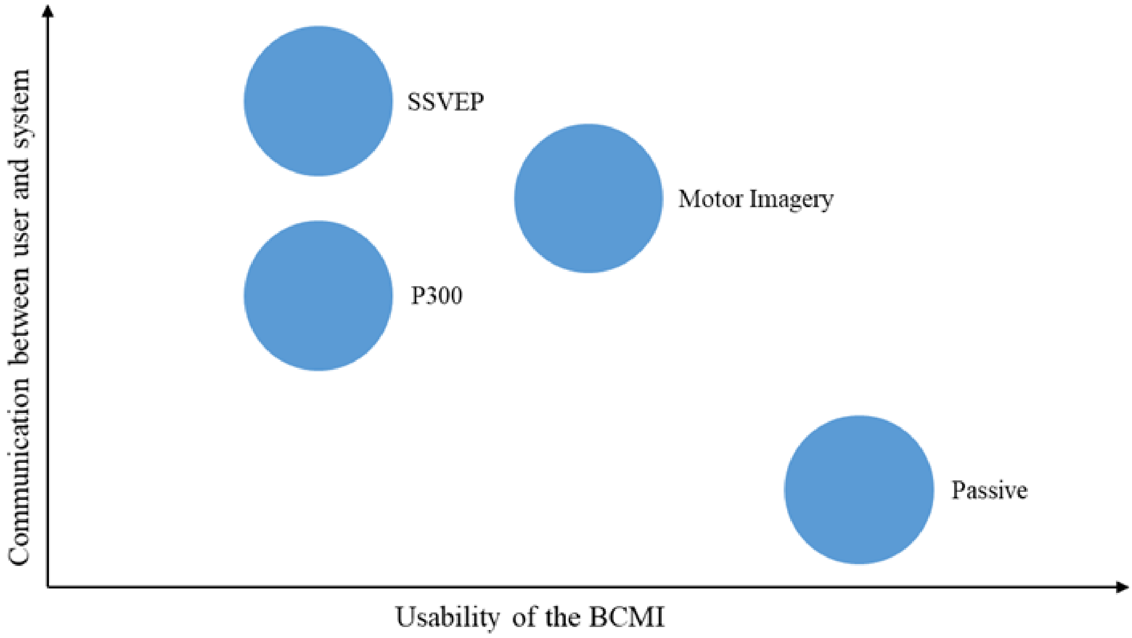


Fig. 2.1 Comparison of BCMIs based on usability of BCMI and communication between user and system. Note that this graph is based on qualitative analysis.

2.6 Paradigms in SSVEP

The visual stimulus for SSVEP can be based on three different principles — (i) time modulated VEP (T-VEP), (ii) frequency modulated VEP (F-VEP), and (iii) code modulated VEP (C-VEP). In T-VEP, each region flashes at an *on* or *off* state. Flickering sequences are designed such that regions are mutually independent (Lee et al., 2006). These are locked in time and phase with the onset of the stimulus (Bin et al., 2009a). As the *on* and *off* states for every region are mutually exclusive, they are required to have low stimulus rates. Moreover, accurate detection requires averaging over multiple trials. Thus, the ITR obtained through T-VEP is about 30 $bits\ min^{-1}$, which is considerably less than the other two techniques (Bin et al., 2009a).

For F-VEP, each region flashes at a unique frequency and evokes the same frequency in the subject's EEG. It can be realised through two platforms — light emitting diodes (LEDs) or a monitor screen. LEDs are controlled by micro-controllers or dedicated circuitry that give them the advantage of accurately flashing at the required frequency. LCD screens, on the other hand, are restricted by the monitor refresh rate because the refresh rate needs to be divisible by the stimulation frequency. For example, in a LCD screen of refresh rate 60Hz, the possible stimulus frequencies are 30, 15, 12, 10, 8.57, 7.5Hz, and so on. However, interfaces are highly customisable with general purpose computers when compared to LEDs.

Alternatively, another useful parameter that is often encoded in the visual stimulus is phase. As mentioned earlier, F-VEPs are phase-locked and time-locked with the stimulus. For instance, by using 15Hz, 4 regions can be presented different with phases of 0, $\pi/2$, π, and $3\pi/2$ (Jia et al., 2011). This is commonly referred to as mixed frequency and phase coding. Nakanishi et al. (2014b) adopted this technique to develop a 32-target BCI-speller, which achieved an ITR of 166.91 *bits min*$^{-1}$. Frequency resolution is an important factor while designing the visual stimulus. As frequencies are placed closer to each other, they are less distinguishable, but offer greater number of choices to the user.

The *on* and *off* states in C-VEPs are based on pseudorandom sequences. Maximum length sequence (m-sequence) is a popularly used technique to generate pseudorandom binary sequences, where 1 and 0 stand for *on* and *off* respectively. There is a unique pattern of binary digits assigned to every region. In this type of system, user-training is required. Bin et al. (2011) developed a 32-target BCI speller and achieved an ITR of 108 *bits min*$^{-1}$. During the training phase, the user is expected to gaze at a particular region and EEG template signals are recorded. In the online version of the system, the user's choice is detected by calculating correlation values between the user's signals and template signals.

For a brief period in BCI research, C-VEPs realised the highest ITRs. However, developments in F-VEP have enabled it to obtain higher communication rates. Manyakov et al. (2013) proposed the use of sinusoidal stimulation as opposed to the conventional *on / off* technique. This study gained popularity as it evoked a more stable phase response in EEG. Chen et al. (2015b) utilised this paradigm to develop a novel stimulation technique, joint frequency-phase modulation (JFPM) and obtained an ITR of 319.2 *bits min*$^{-1}$. The study attributed this multi-fold increase in performance to the stimulation technique. Therefore, this chapter deduces JFPM as the most suitable stimulation technique for SSVEP-based BCMIs.

2.7 Concluding Discussions

This chapter surveyed the different types of BCIs that can be incorporated into computer music. It explored the prospects developing musical interfaces by using an appropriate paradigm. It investigated each category based on two criteria — usability of the BCMI and the communication between user and the system. The first criterion consisted of method of detection of EEG, environmental conditions, and user-centric conditions. The second criterion encompassed communication rate (ITR) and the relation between the activity and the actual application. Each kind BCI possessed exclusive advantages over the other. A passive system realised high usability, P300 provided huge number of choices to the user, motor imagery established a strong relationship between the activity and application, and SSVEP attained very high ITR. However, this thesis aims make BCMIs more usable for practical deployment and improve communication rates. Therefore, framework of comparison was targeted towards finding an appropriate BCI technique that would achieve this objective.

The discussions acknowledged motor imagery and SSVEP as potential approaches for BCMIs. As shown in figure 2.1, the former achieved a good balance between the two criteria of comparison and the latter realised an extremely high ITR. Motor imagery was applicable to musical contexts that required 3 to 5 options. This is practical for applications that control percussion instruments. Contrarily, SSVEP has provided 32 to 40 targets in several studies. This can be useful to build musical systems such as piano interfaces, DJ systems, and composition tools. Considering the current challenges faced by the BCI community and requirements of musical applications, the chapter prioritised ITR over other factors and concluded SSVEP as the most suitable technique.

The chapter also reviewed paradigms in SSVEP. It acknowledged the rapid nature of neurotechnology. It discussed how LEDs were initially used to flicker at the correct frequency and later changed to sinusoidal stimulation through the computer screen. Such advancements open up the opportunity to incorporate these new techniques into computer music. For instance, within the Interdisciplinary Centre for computer music Research (ICCMR), Eaton (2016) created a BCMI by using LEDs and presented 4 choices to the user. Such a system can be modified and deployed on a laptop or tablet. Moreover, *on / off* stimulation can be changed to JFPM to realise greater communication rates. Improvements in usability will be advantageous to patients who are suffering from motor disabilities. For such individuals to use these systems, specialists and engineers are normally required to set-up the system. If there is an improvement in portability and ease of use, the system can be assembled by carers and nurses, who are not experienced with neurotechnology.

Chapter 3

Investigating Methods for Stand-alone Brain-computer Music Interfaces

3.1 Overview

This chapter explores methods to develop stand-alone brain-computer interfaces (BCMIs) based on steady state visually evoked potential (SSVEP). It adopts a dry and wireless electroencephalogram (EEG) headset to improve the portability of BCMI systems. The visual stimulus was created and presented on a laptop by using JUCE, which is a C++ audio application framework. The chapter discusses technical aspects involved in creating the stimulus and a dedicated *thread* to receive data from the headset. Over the years, there have been several developments in visual stimulation techniques and EEG analysis paradigms for brain-computer interfaces (BCIs), which have been incorporated in this chapter. The system was tested on 8 different subjects. A novel and customised filter was designed to increase the signal to noise (SNR) of brainwaves. For a time window of 4s and 2.25s, the mean accuracy of the BCMI was $91.67 \pm 8.87\%$ and $79.17 \pm 13.75\%$ respectively. In comparison to earlier BCMIs, this chapter presents a system that is more portable, increases number of user-available choices to 6, and improves communication rates.

3.2 Introduction

Brain-computer music interfaces (BCMIs) provide a form of musical control that requires no or minimum muscular power. It is beneficial for patients who are suffering from locked-in syndrome, which is the loss of all or most motor abilities, because it offers them a way to experience the realm of music technology. It also allows creative practitioners to communicate with musical applications through a novel mechanism of control. Brain-computer interfaces (BCIs) are generally tested in laboratories with controlled environments. There are many factors that determine the performance of the system. The evaluation framework presented in section 2.3 stressed on the importance of considering environmental and user-centric restrictions while deploying BCIs. This chapter focuses on making SSVEP-based BCMIs more robust and applicable for real-world scenarios. Equipment that is used to detect electroencephalogram (EEG) is normally expensive and bulky. Traditional headsets use multiple layers of wiring, which force them to be attached to the analysing unit (Lin et al., 2008). This causes inconvenience and reduces mobility. Headsets with high electrode densities provide reliable signals, but concurrently increase the manufacturing cost. Additionally, they require greater set-up time. Fundamentally, there are two types of EEG electrodes — wet and dry. The former strengthens contact between the electrode and scalp with the help of gel, which acts as an electrolyte. This is the most popular type of electrode in BCI experiments. It provides excellent quality for non-invasive signals and is ideal for biomedical and physiological research (Searle and Kirkup, 2000). On the other hand, dry electrodes are more convenient because they directly sit on the head without any additional substances. They suffer from lower signal quality and are vulnerable to higher impedances between the electrode and skin. Moreover, LEDs accurately present the visual stimulus, but are not suitable for customisation and larger number of targets. As trends transformed from LED matrices to LCDs, scientists generally presented the stimulus on 21 to 23.6 inch monitor screens (Wang et al., 2017, 2012). Despite them being a more usable alternative to LEDs, these monitors are less portable. For instance, attaching this bulky monitor to a wheelchair would be difficult.

Neuroscientists have pursued the different challenges that are encountered while unfolding this technology. Over the years, various companies have invested in building wireless systems for EEG detection (Hairston et al., 2014). They are generally governed by a proprietary wireless protocol or Bluetooth. The 10-20 International system was originally proposed by Jasper (1958), allowed 21 possible locations on the head. Researchers acknowledged the necessity for higher electrode densities and devised alternative methods like modified combinatorial nomenclature (MCN) and the 10-5 system (Klem et al., 1999; Oostenveld and Praamstra, 2001). For practical deployment of SSVEP, recording signals from all these locations is unnecessary. Instead, highest SNR is achieved in the occipital and parieto-occipital region. For instance, Wang et al. (2008) developed a SSVEP-based BCI that detected EEG from 2 locations — O1 and O2. Therefore, customised EEG headsets can considerably minimise cost. Despite the excellent signal quality from wet electrodes, using them for practical purposes like wheelchairs, prosthesis, computer and musical interfaces, etc. can be time-consuming. In the case of carers who look after locked-in syndrome patients, applying the head is a sophisticated hands-on task and notably increases set-up time of the BCI, especially when there is a higher number of electrodes. Searle and Kirkup (2000) reported the rare occurrences of dermatological responses due to toxicological properties of electrolytic gels. Moreover, the subject's head needs to be cleaned after use. Therefore, studies have been directed towards improving contact between skin and gel-free electrodes. Typically, impedance values are in the range of $150-200k\Omega$ and $5-10k\Omega$ without and with gel respectively (Lopez-Gordo et al., 2014). The performance of dry SSVEP-based systems can be improved by increasing number of electrodes (Lin et al., 2007) and optimising visual stimulation and signal processing techniques (Chen et al., 2015b). This project aims to develop a BCMI that adopts a wireless and dry EEG headset manufactured by Cognionics, Inc. In order to realise bespoke optimisations, all experimental paradigms have solely used this headset and not alternative sensors.

Wang et al. (2011) explored the prospects of exploiting the ubiquity of cell-phones for BCIs. The phone performed the operations of receiving and analysing EEG and auditory feedback. However, the visual stimulus was presented on a 21 inch monitor. Wang et al. (2013) extended the study to develop a stand-alone phone-dialling application which encapsulated all BCI operations into a laptop, tablet, or mobile. The chapter enhanced the prospects of building truly portable BCIs. SSVEP-based BCMIs can be realised in several ways — generate musical phrases, produce audio output of instruments, or a composition tool that remembers previously made choices. However, the operations of BCMIs are often carried out by separate processors. For instance, Eaton (2016) used 2 different laptops to present the visual stimulus and run the musical engine, which is due to the fact that audio processes require dedicated *threads*, which make them computationally demanding to run alongside BCI operations. This thesis aims to develop a SSVEP-based stand-alone BCMI that realises audio output. It proposes the idea of building these systems by using JUCE, which is a C++ application framework used to develop mobile and desktop software. JUCE allows cross-platform development, which would enable the deployment of BCMIs in Windows, Android, Linux, iOS, and macOS. It aims to exploit the ubiquity of these platforms to expand the reach of neurotechnologies. This chapter delves into the technical aspects involved in developing the visual stimulus by using open graphics library (OpenGL) and a driver to receive signals from the EEG headset. It provides the user with 6 choices and adopts joint-frequency phase modulation (JFPM) as the visual stimulation technique. It tests the system on 8 subjects and evaluates the performance based on an offline analysis. Signal processing and filtering techniques have been analysed and a framework for developing an online BCMI has been proposed.

3.3 System Design

As shown in figure 3.1, the operations carried out by BCMIs can be categorised into 4 sub-operations — providing the visual stimulus, receiving EEG signals, analysing the obtained data, and producing audio / musical output. This chapter discusses the details of the first three sub-operations. The specifications of the laptop in this project is *17.3 inch, HP ProBook 470 G4, Windows 10, 8GB RAM, Intel i7 2.7GHz, NVIDIA graphics GeForce 930MX, and Integrated HD graphics 620.*

3.3.1 Visual Stimulus

This subsection is divided into 2 portions — (i) technical specifications of implementing the visual stimulus (ii) Properties of the stimulus.

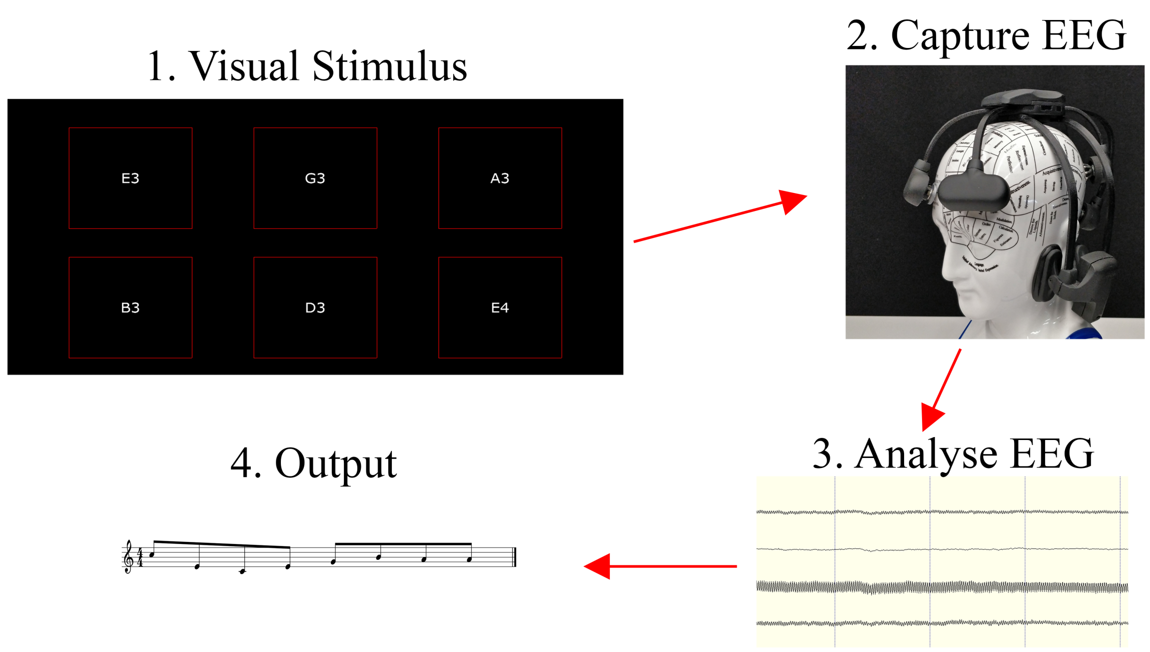


Fig. 3.1 Overview of BCMI system. The symbols in the visual stimulus stand for MIDI notes.

3.3.1.1 Technical Specifications

Fundamentally, there are two possible ways of rendering a graphical user interface (GUI) — central processing unit (CPU) and the graphical processing unit (GPU). On one hand, business applications display objects on the screen by mainly using the CPU. On the other hand, modern computer games utilise the power of the CPU and GPU working in tandem to provide the user with a mesmerising 3D experience. The laptop used in this project has a refresh rate of 60Hz. Therefore, the most straightforward way to implement the visual stimulus is to set a timer thread at 16.67ms and print the visual stimulus by using the CPU. This is not efficient as it can lead to problems like screen tearing (which is a visual artefact). Moreover, Windows 10 is a general purpose operating system and not a real-time operating system (RTOS), which leads to unreliable timing operations (Cecotti et al., 2010; Stankovic and Rajkumar, 2004). SSVEP-based BCIs that present the stimulus on computer screens often take advantage of *hardware accelerated rendering*, in which the computational load is shared between the CPU and GPU. This project harnesses JUCE's support for OpenGL, which is an application programming interface (API) to integrate the GPU (Segal and Akeley, 2018). On systems like mobile phones and tablets, hardware accelerated rendering is obtained through OpenGL ES, which is cross-platform API that comprises most functions of OpenGL.

For SSVEP-based BCIs, it is crucial to obtain vertical synchronisation (VSync). VSync is the process of synchronising the display refresh rate and the frame rate of the application, which has been enabled in the system. It prevents the software from sending more number of frames than the monitor can render. This project adopts sinusoidal stimulation for SSVEP, which was proposed by Manyakov et al. (2013). The flashing stimulus is presented by varying the luminance of the screen, which varies between 0 and 1. The luminance of the target is defined by equation 3.1.

$$s = \frac{1}{2}\{1 + sin(2\pi f_0 t)\} \tag{3.1}$$

where s is the luminance of the region, f_0 is the stimulation frequency, and t is the time. In the programme, t is updated every 1ms. Rhodes (2010) explains the importance of frame-rate independence during game development, where the physics of the game is independent of the refresh rate. This programme realises frame-rate independence. Altering the stimulus between colours of white and black is a popular technique that is used by many studies (Chen et al., 2015a; Nakanishi et al., 2014b; Wang et al., 2017). In other words, luminance value of 1 stands for white and 0 stands for black. In OpenGL, colour is defined with 4 attributes — red, green, blue, and alpha (RGBA). Therefore, based on equation 3.1, the colour output of a specific region can be defined as $\{s, s, s, 1.0\}$.

In computer graphics, instructions to the GPU are passed with the help of a *shader* programme, which is written in a *shading language*. The language used by OpenGL is *OpenGL shading language* (GLSL). In this project, a shader programme has been developed to present the visual stimulus. It is divided into two components — vertex shader and fragment shader. The former specifies the coordinates of the stimulus and the latter denotes the colour.

3.3.1.2 Properties of the Stimulus

SSVEP stimulus frequencies can be categorised into 3 bandwidths — low ($4-12Hz$), medium ($12-30Hz$), and high ($>30Hz$) (Bin et al., 2009a; Regan, 1989; Sözer and Fidan, 2018; Zhu et al., 2010). The spectral peak observed in EEG is the highest for low stimulation frequencies (Chen et al., 2014). The EEG headset in this project uses only 4 dry electrodes and thus, it is essential to choose stimulation frequencies that elicit high SSVEP amplitude. There are two possible ways of choosing stimulation frequencies. One way is to analyse the subject's response to different stimulation frequencies and prepare a set of appropriate frequencies. This method was adopted by Eaton (2016), where the best frequencies were found to be 7, 7.5, 8, and $12.5Hz$ for 4 different choices. It has the advantage of choosing the most optimal set of frequencies. However, the drawback is that it restricts the expansion of choices. The set of optimal frequencies need to be re-calculated for a change in the number of choices. Alternatively, in the second method, regions can be arranged in a fixed interval, such as 7, 7.5, 8, 8.5, $9.0Hz$, and so on. By using this technique, Chen et al. (2015b) developed a 40-target speller in the frequency range $[8, 15.8Hz]$ with a frequency resolution of $0.2Hz$. Considering the headset adopted by this project, such a low resolution may not be feasible. Therefore, this project implements a 6-target interface with the frequencies in the range $[6.0,\ 9.0Hz]$ and a resolution of 0.6Hz. This increases the number of choices when compared the previous system within ICCMR (which is 4, Eaton (2016)). Based on the system's performance with 6 targets, more number of options can be explored in future research.

In JFPM, each target has a unique frequency along with a unique phase. Each region becomes more discriminable because it encompasses two unique attributes instead of one. Hence, equation 3.1 can be modified to include phase features and can be defined as follows.

$$s = \frac{1}{2}\{1 + sin(2\pi f_0 t) + \phi_0\} \tag{3.2}$$

where ϕ_0 is the phase.

Duszyk et al. (2014) conducted a study towards optimising stimulus parameters for SSVEP. There was a strong linear relationship between the size of the stimulus and magnitude of SSVEP, that is bigger the size, greater the spectral peak (Mouli and Palaniappan, 2016). The experiment also revealed that there was no significant relationship with inter-stimulus distance. This chapter considers these factors presents the visual stimulus as shown in figure 3.2. High priority has been given to presenting a large stimulus size and less priority has been given to inter-stimulus distance. Each flashing region is a square of side 3 inches (384 pixels). The horizontal and vertical distances between stimuli are 1.51 inches (192 pixels) and 0.85 inches (108 pixels) respectively.

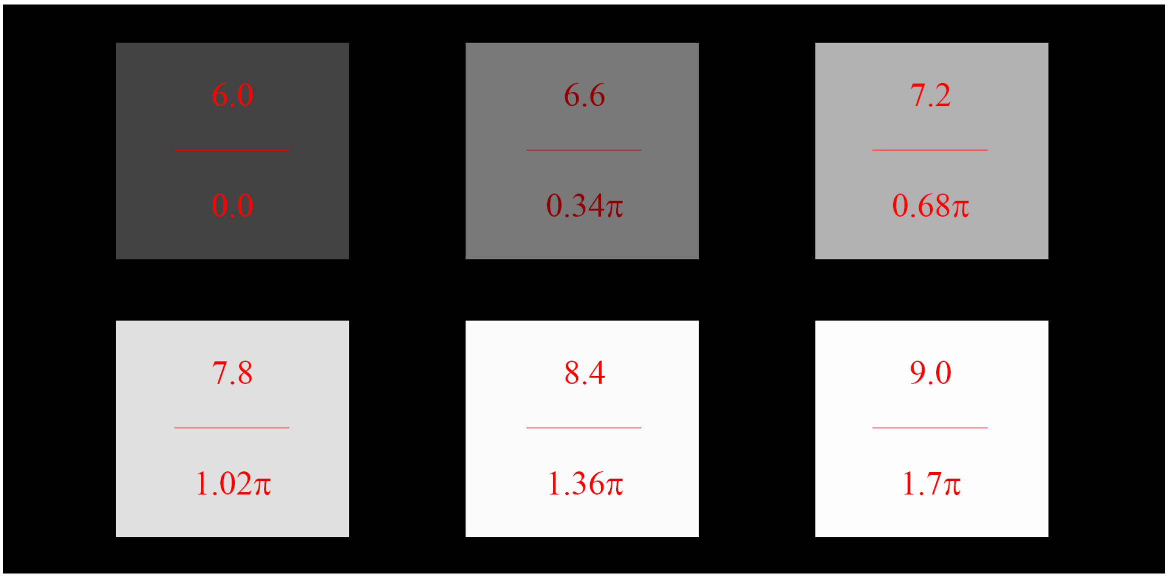
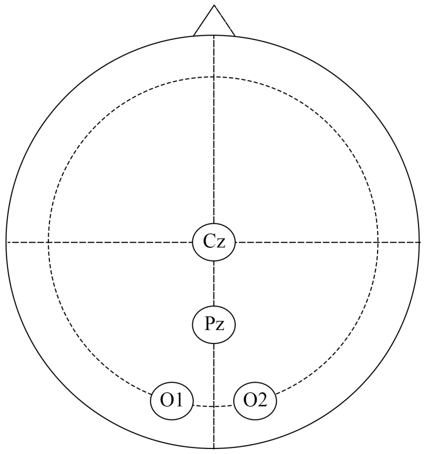


Fig. 3.2 A screenshot of the visual stimulus while the regions are flashing. Note that the text in red colour is only for reference and is not a part of the stimulus. Frequency and phase values of each region are mentioned (frequency is above and phase is below).

3.3.2 Receive EEG

As shown in figure 3.3, the project employs a customised version of the *Quick-20* EEG headset manufactured by Cognionics, Inc, which has a sampling rate of 500Hz. It detects brain waves from four different locations — Cz, Pz, O1, and O2. The headset uses the left earlobe or A1 position as the *reference* electrode. The *ground* electrodes are located at the forehead. The technology developed by Cognionics detects EEG through two different sensors — flex and dry pad sensors (Cognionics Wiki, 2017). Flex sensors are used for regions that contain hair. These are designed to touch the scalp through the hair and obtain acceptable impedance values. Cz, Pz, O1, and O2 are generally hair bearing areas. Dry pad sensors are specifically designed for regions with little or no hair. They attain very low impedances as there is no interference from hair.

The headset transmits data through Bluetooth, which is a wireless protocol. Cognionics provides a data acquisition software to receive EEG signals. However, this project aims to create a stand-alone application, which is independent of third party software. Hence, a dedicated *thread* to receive signals has been written. Each headset is hard-paired with a Bluetooth dongle (shown in figure 3.3b), which can be connected to the USB port of the



(a) The 4 different electrode positions of the EEG headset.

(b) Bluetooth dongle

(c) Components of the headset

Fig. 3.3 EEG headset adopted by this project laptop. The dongle uses a chipset manufactured by Future Technology Devices International Ltd (FTDI). In the system, connection between the dongle and application was established by using the API provided by FTDI.

3.3.2.1 Network Packet

Data recorded by the EEG headset is transmitted through a *network packet*, which is data packaged into one unit. Cognionics Wiki (2014) explains that each network packet contains data recorded by all electrodes at an instant of time. The network follows a serial protocol and each packet contains 27 bytes as shown in table 3.1.

Sl. no.	Byte
1	Packet header
2	Packet counter
3	Cz — MSB
4	Cz — LSB2
5	Cz — LSB1
6	Pz — MSB
7	Pz — LSB2
8	Pz — LSB1
9	O1 — MSB
10	O1 — LSB2
11	O1 — LSB1
12	O2 — MSB
13	O2 — LSB2
14	O2 — LSB1
15	Acc. X — MSB
16	Acc. X — LSB2
17	Acc. X — LSB1
18	Acc. Y — MSB
19	Acc. Y — LSB2
20	Acc. Y — LSB1
21	Acc. Z — MSB
22	Acc. Z — LSB2
23	Acc. Z — LSB1
24	Impedance check
25	Battery voltage
26	Trigger — MSB
27	Trigger — LSB

Table 3.1 Data arrangement within each packet.

Every packet has a *packet header*, which is *0xFF*. The headset is designed such that no other byte can contain this value. The second byte is a *packet counter*, which runs from *0x00* to *0x7F*. It allows the detection of missing packets during transmission. The size of a sample recorded by each electrode is *24bits* or *3bytes*. In order to sequentially transmit data, the reading is split into most significant bit (MSB), least significant bit 2 (LSB2), and least significant bit 1 (LSB1). There are three accelerometers (abbreviated as Acc.) for X, Y, and Z coordinates, which are not considered by the system.

3.3.2.2 Contact between Electrode and Skin

In laboratories, SSVEP experiments are generally performed with electrode impedances under $10k\Omega$ (Bin et al., 2009b; Chen et al., 2015a; Wang et al., 2017). This is easily achievable through wet electrodes. However, the flex sensors adopted by this project offer impedances in the range of $100-2000k\Omega$ (Cognionics, 2018), which is at least 10 times higher than commonly used values. Therefore, there would be a sharp decline in SNR of obtained EEG signals. Contact between the electrode and skin is calculated with the help of a *carrier wave*. A higher *carrier* amplitude corresponds to greater impedance and vice versa. Mathematical formulae to calculate the impedance values from the carrier can be found in Cognionics Wiki (2014). The frequency of the carrier is 125Hz.

As the project adopts dry electrodes, it is relatively straightforward to apply the headset on the subject. Some suggestions (which were empirically observed) for improved signals are stated as follows. The electrodes need to be gently moved around and pressed against the head until an impedance of less than $1000k\Omega$ is attained. The advantage of using these sensors is that their impedances with the skin reduces with the time. Therefore, at regular intervals of time (approximately every minute), the electrodes are lightly pressed against the head (without moving it or changing the position). In all circumstances (for all subjects with varying hair lengths), for all 4 electrodes, a contact of less than $250k\Omega$ was achievable within 10 minutes. The headset provides the option of either disabling or enabling the carrier wave. After obtaining a contact of under $250k\Omega$, the carrier wave was disabled. This would allow full bandwidth of EEG signals with no interference from the carrier.

3.4 Experiment

This section presents an account of experimental procedures and tests conducted with the system. All methods were approved by the ethics committee of University of Plymouth, UK (the details can be found in appendix A). By using MATLAB, the chapter aims to perform an offline analysis over the data collected from experiments.

3.4.1 Set-up

8 subjects (6 males and 2 females) in the age range of [23,55] years participated in the experiments. The experiment was conducted in a dark room. Subjects were asked to perform the experiment bare feet, minimise body movements, and keep electronic gadgets away. During the experiment, subjects were requested to avoid eye blinks. However, there were no methods adopted to detect unintentional eye movements.

6 targets were present on the screen as shown in figure 3.2. A green colour visual cue indicated which target the subject is supposed to look at, which is chosen randomly by the computer. The cue appears for 0.7s and the users are expected to immediately shift their gaze

to the corresponding region. Subsequently, only the borders of the 6 regions are visible for 0.3s. After 1s, all regions flash at their respective frequencies for 4s. Each test case consisted of 12 appearances (or 12 trials) of visual cues (that is, 2 for each target). After a test case, subjects were asked to close their eyes and rest for few minutes. Totally, six test cases were acquired from each user.

3.4.2 Data Analysis

SSVEP exploits frequency-domain characteristics and thus, power spectral density analysis (PSDA) is the most straightforward method of interpreting EEG. A discrete Fourier transform (DFT) can be performed on the signal obtained from any of the occipital or parieto-occipital electrodes. However, non-invasive dry EEG is highly prone to noise. Solely detecting the SSVEP frequency does not lead to reliable performance. Müller-Putz et al. (2005) discovered the presence of harmonic frequencies in SSVEP. For instance, if the subject is gazing at 6.6Hz, then 13.2, 19.8, and 26.4Hz can be observed in the signals. Hence, detecting harmonic frequencies improves the SNR of SSVEPs. Figure 3.4 shows the user's SSVEP response for 6.6Hz. The fundamental frequency and the second harmonic are clearly visible in the graph.

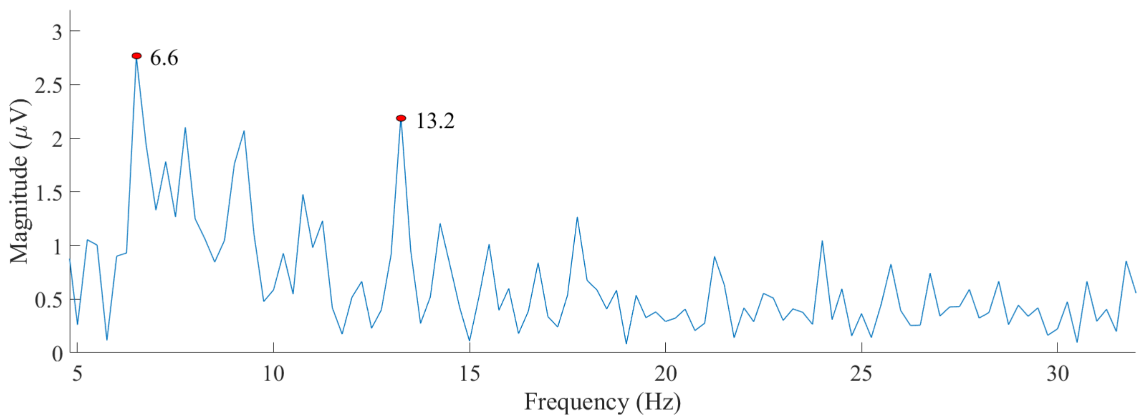


Fig. 3.4 SSVEP recorded from O2 electrode for stimulation of 6.6Hz. Fundamental frequency and second harmonic are marked in the graph.

Alternative signal processing techniques have gained popularity due to improved communication rates. These methods take advantage of recording EEG from multiple channels. Bipolar lead uses an active channel A as well as a reference channel R. The intended signal is $A-R$. In the active channel, the SSVEP amplitude is required to be high and the reference channel needs to have a lower amplitude. It is advantageous if they are placed close to each other because they carry similar noise content (Wang et al., 2004). Therefore, bipolar lead minimises noise in EEG. Lin et al. (2007) proposed the idea of using canonical correlation analysis (CCA), which is based on statistical signal processing. The chapter demonstrated CCA to be more efficient than bipolar lead. CCA is a multi-variate statistical technique that quantifies the relation between 2 sets of variables (Härdle and Simar, 2003). Therefore, unlike bipolar lead, more than two EEG channels can be used for EEG analysis. Let X be a matrix comprising N samples recorded by the EEG headset as shown in equation 3.3.

$$X = \begin{pmatrix} Cz[1] & Pz[1] & O1[1] & O2[1] \\ Cz[2] & Pz[2] & O1[2] & O2[2] \\ \vdots & \vdots & \vdots & \vdots \\ Cz[N] & Pz[N] & O1[N] & O2[N] \end{pmatrix}_{N\times 4} \tag{3.3}$$

Each region in the visual stimulus corresponds to a matrix of reference signals, which consists of the fundamental frequency f_0 and harmonics as shown in equation 3.4.

$$Y = \begin{pmatrix} sin[\frac{2\pi(f_0).1}{f_s}] & cos[\frac{2\pi(f_0).1}{f_s}] & \dots & sin[\frac{2\pi(hf_0).1}{f_s}] & cos[\frac{2\pi(hf_0).1}{f_s}] & \dots & sin[\frac{2\pi(N_h f_0).1}{f_s}] & cos[\frac{2\pi(N_h f_0).1}{f_s}] \\ \vdots & \vdots & & \vdots & \vdots & & \vdots & \vdots \\ sin[\frac{2\pi(f_0).n}{f_s}] & cos[\frac{2\pi(f_0).n}{f_s}] & \dots & sin[\frac{2\pi(hf_0).n}{f_s}] & cos[\frac{2\pi(hf_0).n}{f_s}] & \dots & sin[\frac{2\pi(N_h f_0).n}{f_s}] & cos[\frac{2\pi(N_h f_0).n}{f_s}] \\ \vdots & \vdots & & \vdots & \vdots & & \vdots & \vdots \\ sin[\frac{2\pi(f_0).N}{f_s}] & cos[\frac{2\pi(f_0).N}{f_s}] & \dots & sin[\frac{2\pi(hf_0).N}{f_s}] & cos[\frac{2\pi(hf_0).N}{f_s}] & \dots & sin[\frac{2\pi(N_h f_0).N}{f_s}] & cos[\frac{2\pi(N_h f_0).N}{f_s}] \end{pmatrix}_{N\times 2N_h} \tag{3.4}$$

where f_0 is the stimulation frequency, N is the number of samples recorded from the headset, N_h is the number of harmonics, n indicates sample index, and h stands for harmonic index. CCA finds two weight vectors W_X and W_Y such that the correlation between XW_X and YW_Y is maximised. The dimensions of W_X and W_Y are 4×1 and $2N_h \times 1$ respectively. Correlation is defined by the following equation.

$$r_{AB} = \frac{\sum_{i=1}^{N}(a_n - \bar{a})(b_n - \bar{b})}{(N-1)s_a s_b} \tag{3.5}$$

where $A = XW_X$, and $B = YW_Y$, $r_{A\,B}$ is the correlation between A and B, a_n belongs to A, b_n belongs to B, N is the number of samples, $\bar{a}$ is the mean of A, $\bar{b}$ is the mean of B, s_a is the standard deviation of a, and s_b is the standard deviation of b. There are two ways in which CCA can be used for BCIs — supervised and unsupervised. In the former, weight vectors are calculated over multiple trials and then averaged. In unsupervised detection, solely the correlation value and weight vectors for that specific trial are used. The target with the highest correlation value is considered to be the choice of the user. This chapter uses unsupervised CCA and hence, would avoid time-consuming procedures like user-training. MATLAB's *canoncorr* function was used to calculate CCA. Furthermore, phase is not detected during analysis. However, having a unique phase makes the flashing regions more discriminable while the user is gazing at them.

The amount of data required to accurately analyse EEG depends on numerous factors — frequency resolution, quality of EEG signals, number of electrodes, etc. According to communication theory, for a resolution of Δf, a data length of $1/\Delta f$ is required to meet orthogonality condition (Chen et al., 2015b; Rappaport, 2001). There are two aspects in SSVEP-based BCIs that make them disagree with this principle — (i) if there is more noise content in EEG, then more time is required, (ii) detection of harmonic frequencies increases speed (because $1/2\Delta f$ is less than $1/\Delta f$). Therefore, this chapter records SSVEPs for 4s, which is long enough to meet orthogonality between stimulation regions. Moreover, in visual-based systems, a visual latency of 7 to 15ms is generally observed (Fransson, 1966). During analysis, this study discarded the first 20ms of EEG data after the onset of the stimulus.

3.4.3 Filtering

Figure 3.5 shows EEG signals recorded from the O2 electrode. As you can observe, the global maximum of the graph is under 1Hz. In this system, frequencies below 6Hz are sources of noise in SSVEPs. Moreover, a peak at 50Hz was detected, which can be attributed to the electric hum. Considering the fact that the headset is wireless, this is an uncommon issue. However, this noise was observed in most EEG recordings. In earlier research, Chen et al. (2015a) proposed the use of filter banks (which is an array of band-pass filters) to improve communication rates of BCIs. However, the design of the band-pass filter involves a high-pass and low-pass filter in cascade. In order to achieve a steep roll-off in the low-pass filter, it generally requires a very high filter order, which is computationally expensive. Therefore, this chapter uses two filters in cascade — high-pass and notch filter. It predicts that the effect of a low-pass filter for SSVEP is not noticeable.

Finite impulse response (FIR) filters have linear phase, but in order to achieve a sharp magnitude response, it requires a high Q-factor (Taylor, 1983). This increases the computational cost, which might not be suitable for a stand-alone BCMI. Contrarily, infinite impulse response (IIR) filters are computationally inexpensive to implement, but have non-linear phase. Phase distortion might hinder the performance of the BCI because phase is encoded in the flashing regions. Therefore, this project adopts zero phase filtering, where the signal is filtered forward and then backward, resulting in no phase distortion (Gustafsson, 1996). MATLAB's *filtfilt* function was used for this operation. In order to obtain a steep roll-off in the frequency response, Chebyshev and elliptic filters are have been used in BCI literature (Chen et al., 2015a; Duszyk et al., 2014). However, this is done at the cost of pass-band ripple in the output, which might be counterproductive in dry EEG (due to low SNR). Thus,

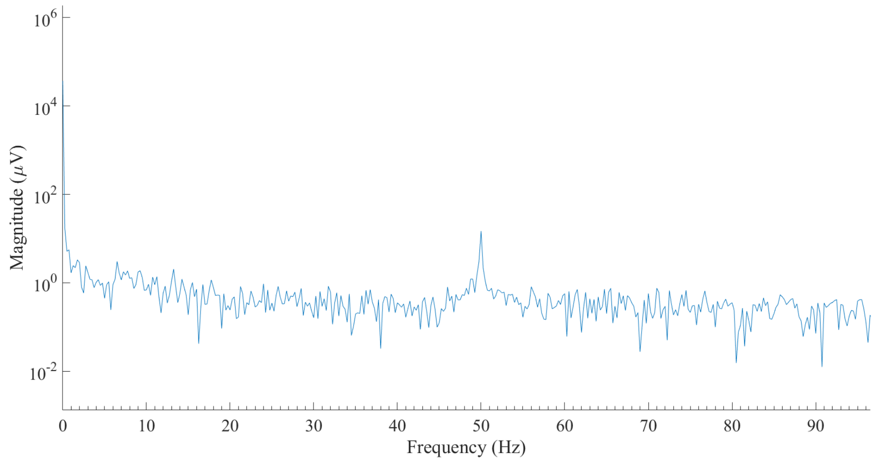


Fig. 3.5 EEG recorded from O2 electrode for a stimulation frequency of 6.6Hz without filtering.

this thesis incorporates Butterworth filters. The high-pass and notch filters were set at 4Hz and 50Hz respectively. Their filter orders are 6 and 2 respectively. Figure 3.6a shows the combined response of the filters and figure 3.6b reproduces figure 3.5 after filtering.

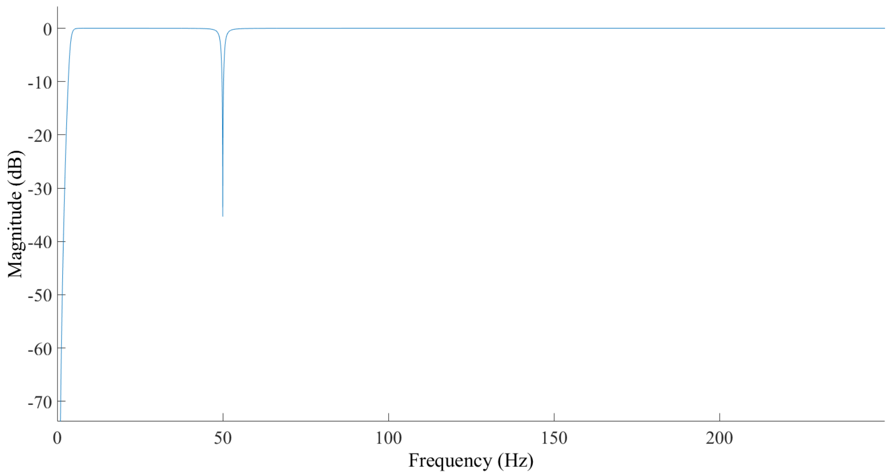
3.5 Results

3.5.1 Feedback from subjects

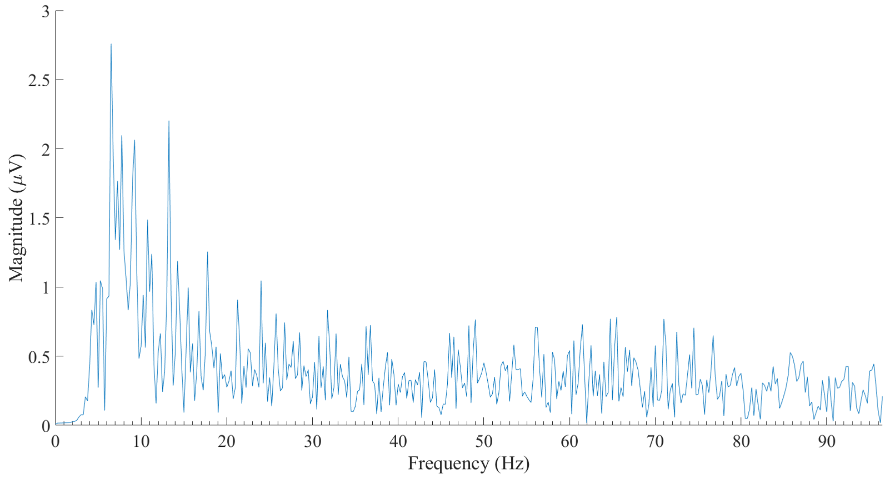
8 subjects referred to as S1 to S8 participated in the experiments. S1 and S4 were experienced with SSVEP-based BCIs and the rest were BCI novices. S2, S7, and S8 stated that that the flashing regions were very closely placed. It was difficult to independently gaze at the required target due to interference from other flashing regions. Remaining 5 subjects said that the visual stimulus design was comfortable. S1 and S6 experienced physical pressure from the Cz electrode. This is due to the fact that the weight of the entire headset rests on that electrode. It caused minor discomfort to the subjects, but it was viable for the duration of the experiment.

3.5.2 Harmonics and Filtering

As mentioned earlier, harmonic components improve the performance of BCI systems. In order to find the optimal number of harmonics (N_{h}), accuracy vs time graphs were plotted for $N_{\mathrm{h}} = [1, 10]$. The accuracies of test cases obtained from all the subjects were collectively



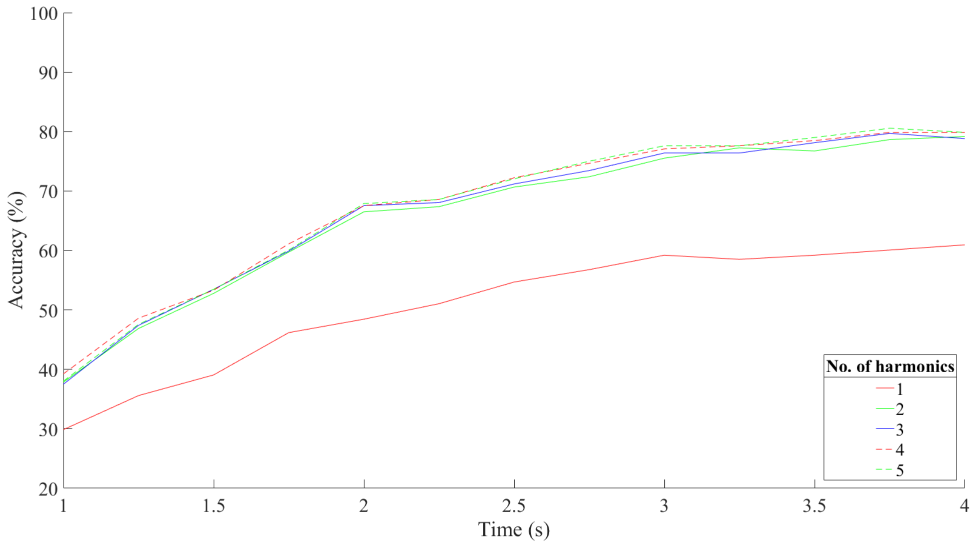
(a) Magnitude vs frequency plot of the filter applied to EEG signals.



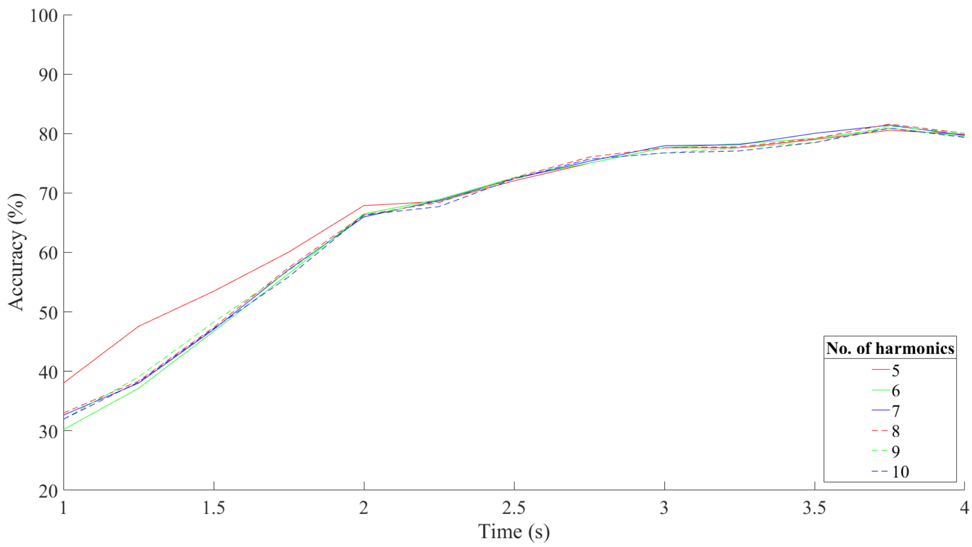
(b) SSVEP response for 6.6Hz after filtering.

Fig. 3.6 Filtering in BCMI system.

averaged. Figures 3.7 and 3.8 illustrates the performance of the system without and with filtering respectively.



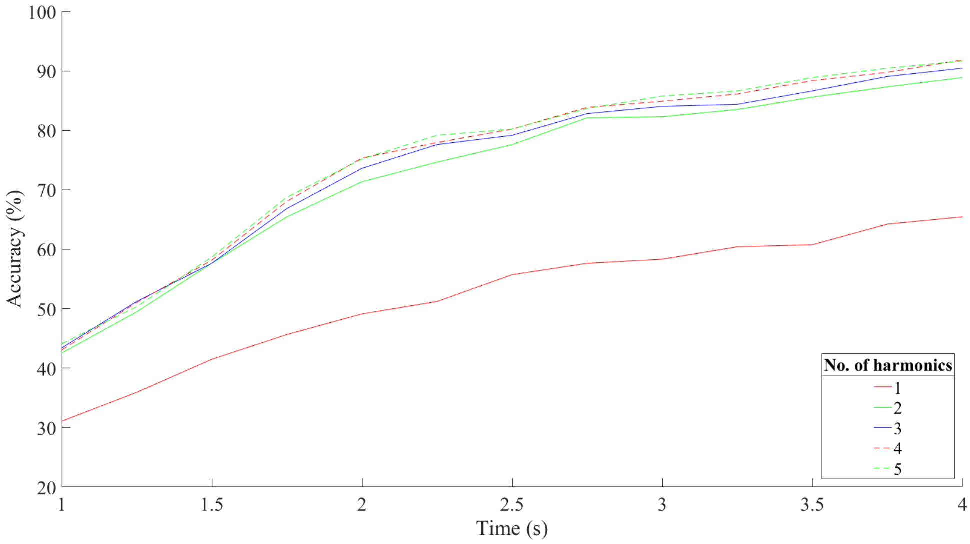
(a) Accuracy vs time for N_h = [1,5] without filtering.



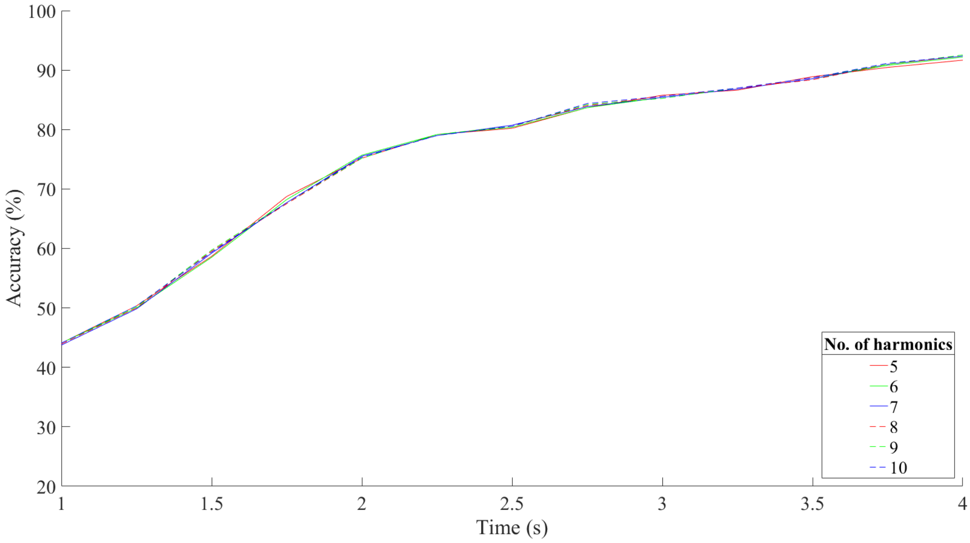
(b) Accuracy vs time for N_h = [5,10] without filtering. $N_h = 5$ performs better than higher harmonic values due to the absence of the notch filter.

Fig. 3.7 Averaged performance of BCMI system without filtering.

For both with and without filtering, $N_h = 5$ appears to be the optimal value. There is a noticeable increase in performance from N_h values of 1 to 3. For N_h values of 3 to 5, there is a slight increase in performance. However, as you can observe in figures 3.7b and 3.8b, there



(a) Accuracy vs time for N_h = [1,5] with filtering.



(b) Accuracy vs time for N_h = [5,10] with filtering.

Fig. 3.8 Averaged performance of BCMI system with filtering.

is no noticeable difference in performance for N_h values greater than 5. Therefore, this thesis deduces 5 as the optimal value for N_h.

As you can observe in figures 3.7 and 3.8, filtering considerably improves the performance of the system. For a data length of 2.5s, the accuracies are 72.05% and 80.21% for without and with filtering respectively. For a data length of 4.0s, the accuracies are 79.86% and 91.67% for without and with filtering respectively. Hence, an improvement of about 10% was observed with the application of the filter.

3.5.3 Individual Performance

This subsection analyses the individual performances of subjects for filtered EEG and $N_\mathrm{h} = 5$. Figures 3.9 and 3.10 illustrate accuracy vs time graphs for all subjects. As you can observe, there is an increase in accuracy with data length. For 4s time window, all subjects excluding S6 and S8 attained an accuracy of greater than 90%. S6 and S8 realised an accuracy of 87.5% and 70.83% respectively. Table 3.2 tabulates the accuracy values for time window of 4s. It is important to note that S8's accuracy is considerably lower than the other subjects. The next chapter aims to minimise inter-subject variation in performance.

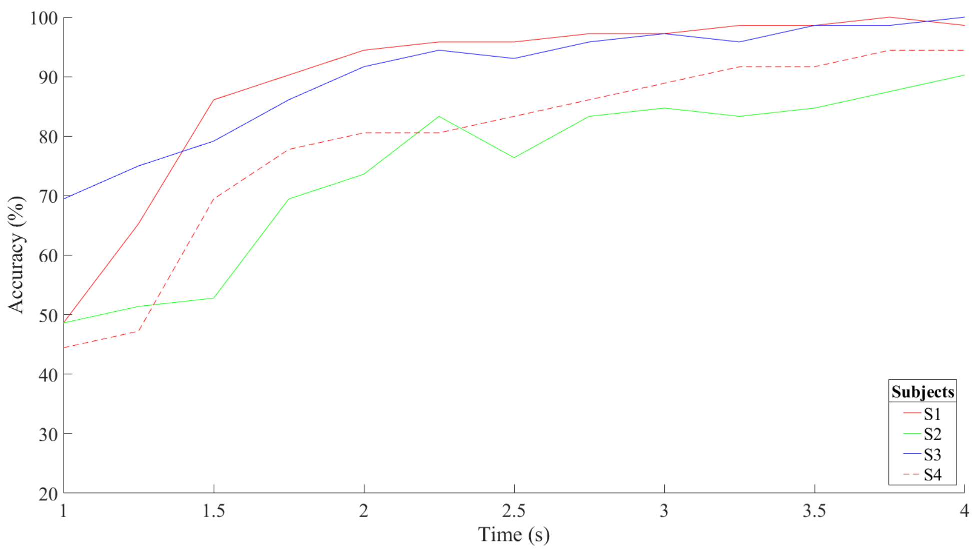


Fig. 3.9 Accuracies of subjects 1 to 4. Values were calculated in steps of 0.25s.

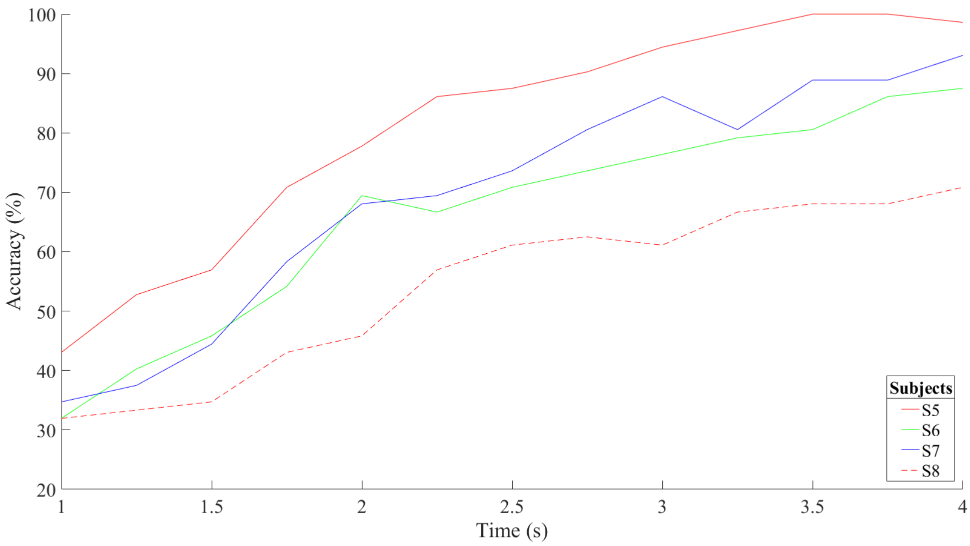


Fig. 3.10 Accuracies of subjects 5 to 8. Values were calculated in steps of 0.25s.

Subject	Accuracy (%)
S1	98.61
S2	90.28
S3	100
S4	94.44
S5	98.61
S6	87.5
S7	93.06
S8	70.83
Mean	91.67 ± 8.87

Table 3.2 Accuracy of all 8 subjects for time window of 4s.

3.6 Information Transfer Rate

Information transfer rate (ITR) is a widely adopted metric that is used to evaluate the performance of BCIs. It is a contraction of accuracy, speed, and number of targets, which enables us to choose an optimal time window for the system. It has been defined in Wolpaw et al. (2002, 1998) by the following mathematical formula (Chen et al., 2014; Yuan et al., 2013).

$$ITR = \frac{60}{T}\left[log_2 N + plog_2 p + (1-p)log_2\left(\frac{1-p}{N-1}\right)\right] \quad (3.6)$$

where T is the trial time in seconds, N is the number of flashing regions, and p is the accuracy divided by 100.

While calculating ITR, it is important to consider the relax time between successive trials. In this system, a test case consisted of 12 trials and a relax time of 1s was given between each trial. During the relax time, the user shifts the gaze from one target to another. For instance, after the user gazes at the target for 4s, the regions stops flashing for 1s, during which the user shifts the gaze. ITRs for all subjects were averaged and plotted in figure 3.11. The graph reveals that 2.25s is the optimal window for the BCMI. Table 3.3 tabulates the ITR and accuracy values of all subjects for a time window of 2.25s. 2 subjects realised accuracies of around 95%, 3 were between $80-90\%$, and 3 were below 70%. This reveals that that 2.25s is not an optimal window for all subjects. Instead, subject-specific time windows will be more suitable for this system.

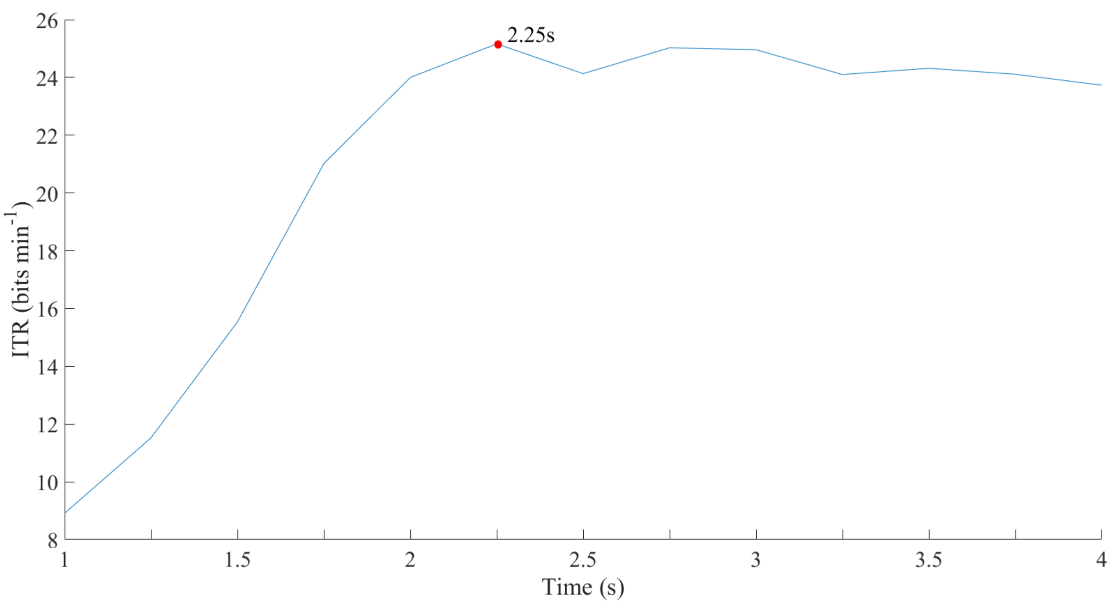


Fig. 3.11 Average ITRs of all subjects for different time windows.

3.7 Discussion

The previous SSVEP-based BCMI system developed within the Interdisciplinary Centre for Computer Music Research (ICCMR) had 4 choices provided to the user (Eaton, 2016). By using research grade Sahara g.tec headsets, the system realised an accuracy of $90.91-96.36\%$ and an average response time of 3.88s. However, when the project explored the use of a commercial and wireless headset (which is the Emotiv epoc EEG wireless headset), it

Subject	ITR (bits min^{-1})	Accuracy (%)
S1	42.93	95.83
S2	28.58	83.34
S3	39.62	94.44
S4	26.27	80.56
S5	31.04	86.11
S6	16.48	66.67
S7	18.23	69.44
S8	11.06	56.94
Mean	26.78 ± 11.17	79.17 ± 13.75

Table 3.3 Accuracy of all 8 subjects for time window of 2.25s.

realised an accuracy of 60%. This is probably be due to detecting EEG with only one electrode. Moreover, harmonic components of SSVEP were not considered for analysis. The previous section of this chapter demonstrates the reliability of the Cognionics EEG headset for SSVEP-based experiments. The communication rates obtained by this chapter surpasses the performance of previous BCMIs with medical grade EEG headsets. This improvement of performance is due to the following reasons — (i) increase in number of choices to 6, (ii) Employing JFPM as the visual stimulation technique, (iii) Using CCA to analyse EEG, and (iv) application of filters. Therefore, this chapter contributes to answering RQ2.

For data lengths of 4s and 2.25s, the standard deviations are 8.87 and 13.75 respectively. This implies that a common time window for all subjects might not be favourable. Therefore, user-specific optimisations might contribute to improved communication rates. The variation in inter-subject performance can be due to three reasons — (i) different physiological responses of subjects to SSVEP (Guger et al., 2012), (ii) inexperience of using the BCMI, and (iii) experimental set-up of the BCMI. The first factor is beyond the scope of this thesis. The second reason can be addressed by arranging user-training sessions with the BCMI. The third factor opens up interesting possibilities to optimise the system. S2, S7, and S8 felt that the flashing regions were very close to each other. Perhaps, their performance can be improved by reducing the size of the flashing regions and increasing the distance between them. The configuration of the Cognionics headset might not be suitable for all head sizes. For instance, O1 and O2 electrodes might not be reaching the occipital regions of the respective subjects.

ITR might not be the best method to evaluate musical applications. For instance, a BCMI that triggers piano samples based on the user's choice might require a small time window.

Contrarily, if the system is outputting musical phrases (which is a series of notes), it will be advantageous to have a bigger time window.

3.8 Conclusion

This chapter investigated methods to develop stand-alone BCMIs and supported answers to RQ1 and RQ2. It proposed the use of an audio application framework called JUCE to develop these systems on platforms like laptops, tablets, cell phones, etc. The ubiquity of these platforms can be exploited to widen the outreach of neurotechnologies. Out of the 4 different operations carried out by BCMIs, 2 operations were encapsulated into a multi-threaded programme — providing visual stimulus and detecting EEG. Collectively, by implementing these functions, the chapter contributes to answering RQ1, which aims to make BCMIs more usable for real-world scenarios. The visual stimulus was developed with the help of OpenGL alongside vertical synchronisation. It adopted sinusoidal stimulation which was controlled by a dedicated timer thread. OpenGL *shader* programmes were written to harness the computational power of the GPU. The system adopted a dry and wireless EEG headset manufactured by Cognionics, Inc., which detected brainwaves from four regions — Cz, Pz, O1, and O2. Few methods to obtain optimal signal quality were discussed. A bespoke *thread* was created to receive data from the headset.

The experiments in the chapter confirmed that a small screen like the 17.3 inch laptop and a dry EEG headset is suitable for SSVEP-based BCIs. An offline analysis was performed in MATLAB. The chapter incorporated canonical correlation analysis (CCA), which has proven to be more robust than bipolar lead (Lin et al., 2007). It focused on unsupervised analysis of EEG, which allowed the system to operate without user-training. The experiments revealed that the optimal number of harmonics (N_{h}) is 5. This agreed with findings in Chen et al. (2015a). This chapter also devised a customised filter that eliminated noisy low frequencies and the 50Hz hum. It was demonstrated that filtering greatly improved the performance of the BCMI. Considering the fact that the system used dry EEG, it realised high communication rates (mean ITR of 26.78 ± 11.17 *bits min*$^{-1}$) and thus, answering RQ2. In addition to filtering, this improvement was credited to using joint frequency-phase modulation (JFPM) as the visual stimulation technique and CCA as the analysis paradigm.

The dataset attained a low standard deviation for a time window of 4s, but a higher deviation for 2.25s. This established that the optimal time window might not be common for all subjects. User-specific improvements might increase communication rates, which would make the BCMI more universal. These facts call for the need of evaluating the experimental set-up of the BCMI. They embody the foundation for the next chapter in thesis, which would focus on optimising biomedical engineering-based parameters. It may explore different visual stimulus sizes, which might minimise the inconveniences caused to some subjects. Furthermore, 2 more operations — analysis of EEG and producing audio output need to be incorporated within the JUCE application. After doing so, an online BCMI system which is independent of any third party applications would be created.

Chapter 4

Building Musical Systems By Using Optimal Parameters

4.1 Overview

The focus of this chapter is twofold — improving the communication rates of the steady state visually evoked potential (SSVEP)-based system proposed in chapter 3 and developing a stand-alone brain-computer music interface (BCMI). The former is achieved by considering two parameters of optimisation — placement of the electroencephalogram (EEG) headset and size of the visual stimulus. This chapter finds the most suitable configuration of these parameters and demonstrates their impact on the performance of the system. It analyses user-specific factors in order to make the BCMI more universal and usable to a wider range of subjects. In comparison to the system in the previous chapter, the performance of the BCMI has been greatly improved. For a time window of 4s and 2s, the mean accuracies of the BCMI are $97.92 \pm 2.22\%$ and $88.02 \pm 9.30\%$ respectively. The ITR obtained in this chapter is 36.56 ± 9.17 *bits min*$^{-1}$, which is considerably higher than the results in chapter 3.

The second objective of this chapter is achieved by encapsulating all BCMI-related operations into one application. Procedures to analyse EEG include sophisticated mathematical operations, which have been developed within the C++ application framework. JUCE offers dedicated classes for audio playback, which have been used for the system's output. The chapter creates a multi-screen BCMI that encompasses a novel control flow. Music-related icons have been displayed to improve the interactivity of the system. The user is allowed to choose between different musical libraries and trigger different sounds.

4.2 Introduction

Steady state visually evoked potential (SSVEP) is a popularly used technique to develop brain-computer interfaces (BCIs) that are based on gaze-control. Scientists have stated that the method is easy to use and realises high communication rates. (Wang et al., 2011). Physiological characteristics of SSVEP have shown inter-subject variation with respect to amplitudes and stimulation frequencies, to name but two (Bin et al., 2009b). Therefore, this opens up opportunities to optimise subject-specific parameters while deploying BCIs, which would improve the universality of this technology. Wang et al. (2006) implemented user-specific optimisations with respect to three parameters — (i) electrode location, (ii) stimulus frequency, and (iii) speed of selection. Wang et al. (2008) used subject-specific electrode placement to achieve high SNR and thus, highlighted the first parameter. Eaton (2016) utilised optimal stimulation frequencies to develop a SSVEP-based brain computer music interface (BCMI). The previous chapter of this thesis clearly demonstrated the importance of considering the third parameter. In this project, we adopt a dry and wireless electroencephalogram (EEG) headset manufactured by Cognionics, Inc to capture brainwaves and a laptop to present the visual stimulus. It detects brainwaves from 4 different regions of the scalp. Due to the fixed construction of the headset, it restricts options for customised electrode placement. Moreover, the BCI literature is sparse with respect to optimising parameters for dry and wireless headsets. Therefore, the focus of the current chapter lies on enhancing the hardware framework of this project and analyse inter-subject variation to improve performance. Section 3.5.1 discussed the feedback obtained from subjects during experiments. Some users observed interference from neighbouring flashing regions due to peripheral vision. This problem can be addressed by increasing inter-stimulus distance. However, the psychological observations made by subjects might not be in tandem with the physiological properties of SSVEP. Thus, this chapter studies performance of different subjects for varying stimulus sizes.

The next part of this chapter develops an online BCMI after optimising experimental parameters. In chapter 3, two operations in the BCMI were implemented within the JUCE framework — providing visual stimulus and receiving EEG. This chapter develops the remaining two operations — analysing EEG and audio output. Section 3.5.2 demonstrated that filtering improves the performance of the BCMI. In order to prevent phase-distortion, zero-phase filtering was implemented in MATLAB. Moreover, canonical correlation analysis (CCA) involves complex mathematical calculations like inverse square roots and *eigendecompositions* of matrices. These sophisticated signal processing algorithms are generally implemented on high-level programming languages like Python and MATLAB. As this project uses a C++ application framework, it requires an in-depth explanation on how these algorithms are implemented. Audio output has been realised with the help of dedicated classes provided by JUCE. After encapsulating all BCMI-based operations into one module, this chapter proposes a novel musical system, which encompasses a bespoke control flow. The advantage of using audio is that it purely depends on sound samples. Therefore, different musical tones, soundscapes, timbres, instruments, arpeggios, etc. can be explored. The chapter concludes by discussing on how BCIs can be creatively harnessed to develop applications for music technology.

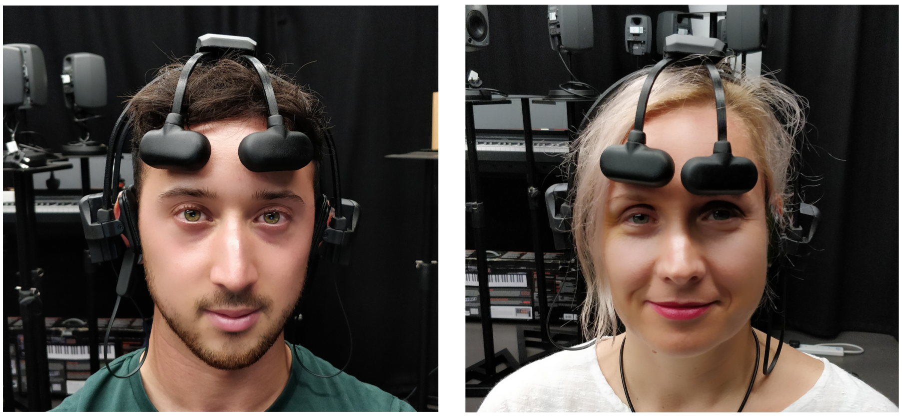
4.3 Parameters for Optimisation

There are two different parameters that are explored for optimisation — placement of headset and size of the flashing regions, which are explained as follows.

4.3.1 Headset Placement

Highest signal to noise ratio (SNR) for SSVEP is generally obtained from the occipital and parieto-occipital regions (Chen et al., 2015b; Wang et al., 2008). In the 10-20 international system, it is important to identify the distance between the *nasion* and *inion*. Let us consider this distance to be *D*. The occipital region is located at 10% of D above the inion (Rowan and Tolunsky, 2003). The headset adopted by this project detects EEG from two electrodes in the occipital region and one electrode in the parietal area. Every subject who uses the headset is expected to have a unique head size. The electrodes might not reach the required locations on the head. Hence, using the same headset for all users might lead to a compromise in performance.

Exploring different headsets is beyond the scope of this thesis. Instead, this chapter aims to delineate a favourable headset placement for users. Cognionics Wiki (2017) does not address this factor. Many images and video demonstrations suggest that the ground dry pad sensors are to be placed at the middle region of the forehead. Let us consider this configuration to be *placement I* as shown in figure 4.1a. In *placement II*, the ground dry pad sensors are placed as high as possible on the forehead, but making sure that the sensors are not placed on hair (as shown in figure 4.1b). The chapter predicts that for *placement I*, the electrodes might not reach the occipital regions of the user's head as shown in figure 4.2a. Therefore, *placement II* has been proposed. The subsequent section conducts tests to analyse the BCI performance under different headset placements.



(a) EEG headset deployed on subjects according to *placement I*.

(b) EEG headset deployed on subjects according to *placement II*.

Fig. 4.1 Two different headset placements on subjects.

(a) Electrode positions for *placement I*. (b) Electrode positions for *placement II*.

Fig. 4.2 Rear view of a subject wearing the headset for different placements.

4.3.2 Stimulus Size

Duszyk et al. (2014) demonstrated that there is a linear relationship between the size of the stimulus and SSVEP amplitude. The previous chapter incorporated this finding and presented flashing regions that are as large as possible within the laptop screen (that is, squares of side 3 inches). S2, S7, and S8 felt that the neighbouring flashing regions were interfering with their central vision and thus, preventing them from being able to gaze at the target region. However, the user's psychological observation may or may not be concurrent with their physiological responses. Moreover, Ng et al. (2012) conducted experiments to study the stimulus specificity of SSVEP-based systems. Contrary to the findings in Duszyk et al. (2014), the study observed a relationship between inter-stimulus distance and classification accuracy. Inter-stimulus distance was quantified with the help of visual angle. For small visual angles, it is defined in Baird (1970); McCready (1985) by the following equation.

$$V = tan^{-1}\left(\frac{S}{D}\right) \tag{4.1}$$

where V is the visual angle, S is the size of the object, and D is the distance between the eye and the object. Ng et al. (2012) concluded that the optimal separation between stimuli was between 5° and 7°. The article also reported poor performance of the BCI for a distance between 2° and 3°. In these experiments, the laptop screen was placed approximately 70cm from the user. Thus, in chapter 3, the system observed a horizontal and vertical gap of 3.13° and 1.76° respectively between stimuli. This chapter re-designs the interface to have equal horizontal and vertical distances, which is equal to 2.75 inches (350 pixels) and therefore, subtending an angle of 5.70° with the eye. Each flashing region was reduced in size to a square of side 1.81 inches (230 pixels) and it subtends an angle of 3.75° with the eye. However, the new stimulus design may or may not be favourable for subjects. Therefore, this chapter conducts tests on different users to evaluate the 2 stimulus designs.

4.4 Experiment

4.4.1 Set-up

The experimental set-up is identical to the methods followed in section 3.4.1. S6 was unavailable for this experiment and a new subject S9 participated in the experiment. The focus of this chapter is to study the effect of headset placement and size of the visual stimulus. Hence, the system is tested with 4 different configurations — (i) *placement I* and big stimulus (ii) *placement I* and small stimulus (iii) *placement II* and big stimulus, and (iv) *placement II* and small stimulus. There are two test cases[1] conducted for each configuration. 6 subjects (S1, S2, S4, S5, S8, and S9) have participated in testing all four configurations. After finding an optimal configuration, the system is tested on S3 and S7.

4.4.2 SNR

In order to compare the 4 different configurations of the system, SNR is employed as one of the methods. The procedure to calculate SNR has been adapted from Chen et al. (2014); Wang et al. (2012). Let k = [1,6] correspond to the six flashing regions. After applying the filter in section 3.4.3, fast Fourier transform (FFT) is performed. The signal is zero-padded to obtain a frequency-resolution of 0.2Hz. Let P(k) be the power at the fundamental frequency of the flashing region. SNR of a specific flashing region r is the ratio of the power at r and the power at the remaining regions, as shown in the following equation.

$$SNR(r) = \frac{5 \times P(r)}{[\sum_{k=1}^{6} P(k)] - P(r)} \tag{4.2}$$

Data is collected from all subjects and SNR values are averaged across all four electrodes. SNR vs stimulation frequency graphs are plotted in section 4.5.2.

4.4.3 Accuracy

EEG data is recorded from subjects for 4 seconds. The previous chapter demonstrated that the accuracy of the system generally improved with an increase in data length. Hence, accuracy vs time graphs are plotted in section 4.5.3 in order to study the performance of different configurations.

4.5 Results

4.5.1 Feedback from Subjects

S5 stated that the bigger stimulus was more convenient because it was easier to focus. 5 subjects (S2, S3, S7, S8, and S9) felt that the smaller stimulus was more comfortable because there was less interference from the neighbouring flashing regions. S1 and S4 were neutral towards the size of the stimulus, but agreed to the notion that bigger stimuli can cause more visual fatigue with the passing of time. S2, S4 and S9 reported discomfort because of the

[1]Each test case consists of 12 appearances of visual cues, which corresponds to 2 appearances for each flashing region. Refer to section 3.4.1 for more details.

Cz electrode. Moreover, S2 and S4 did not notice the Cz electrode in experiments of the previous chapter. This suggests that the headset can be deployed such that the inconvenience from the Cz electrode is avoided.

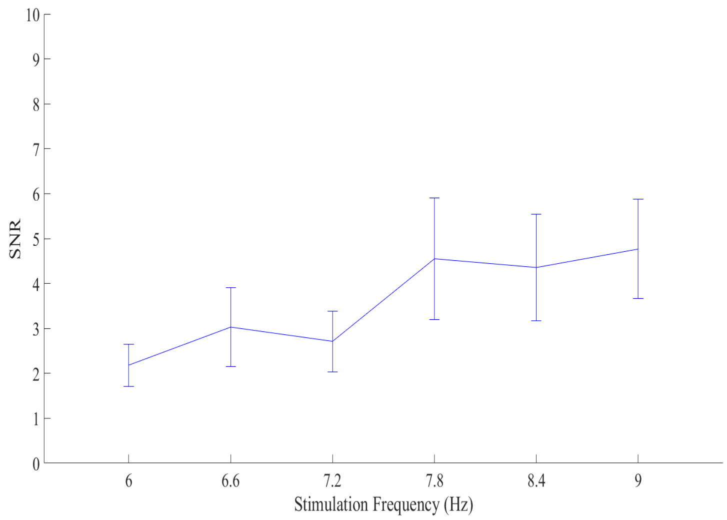
4.5.2 SNR

Figure 4.3 plots SNR vs stimulation graphs for all 4 configurations. Configurations I and II clearly have lower SNRs when compared to configurations III and IV. This reveals that *placement II* provides improved signal quality for SSVEP when compared to *placement I*. Furthermore, the graphs illustrate similar SNR values for different stimulus sizes. This discloses that stimulus size does not have obvious effect on SNR. The SNRs for all stimulation frequencies are averaged and the values for the 4 different configurations are 3.60, 4.25, 5.02, and 5.31 respectively. The smaller stimulus size seems to realise a higher SNR, but not by a great margin.

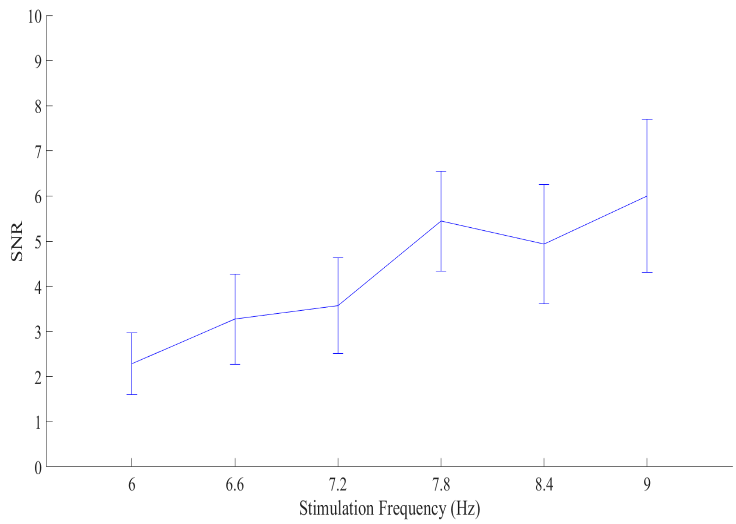
In order to analyse the individual performance of subjects for different configurations, the mean SNR is tabulated in table 4.1. The table reveals that for all subjects, *placement II* either performs better than *placement I* or there is no noticeable difference. Hence, *placement II* can be universally used for all subjects. This demonstrates the effect of head size on SSVEP. Furthermore, it is interesting to note that S8's head size is larger than the remaining subjects, which might be the reason for comparatively low SNRs. The size of the stimulus was dependent on the subject. Different sizes performed better for different subjects. In the previous chapter, S2 and S8 had reported that the stimuli were placed too close to each other. The small stimulus performed better for S8, but there was no difference for S2. Hence, the psychological opinion of subjects might not always reflect in their physiological responses in SSVEP.

	Mean SNR			
Subject	**Config. I**	**Config. II**	**Config. III**	**Config. IV**
S1	4.36	6.08	5.07	6.03
S2	3.33	3.64	3.98	3.56
S4	2.54	3.08	3.43	3.85
S5	3.38	3.49	5.80	5.33
S8	1.42	1.71	1.38	2.01
S9	6.56	7.50	10.47	11.09
Mean	3.60	4.25	5.02	5.31

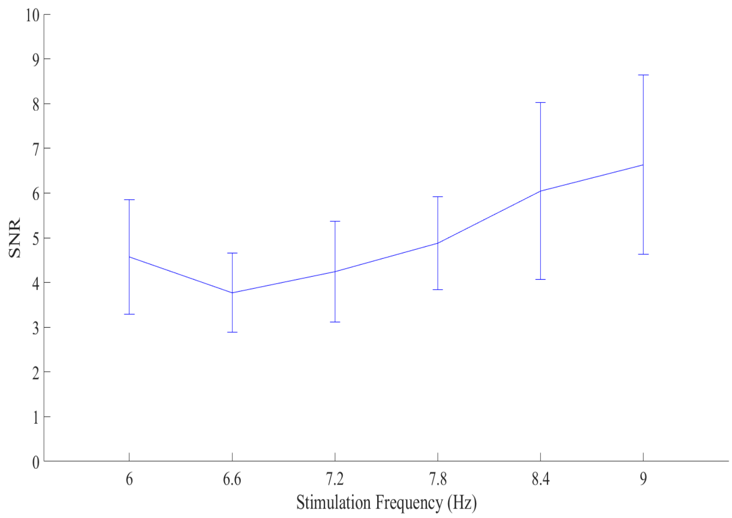
Table 4.1 SNRs averaged over all EEG channels and stimulation frequencies for each configuration (config.).



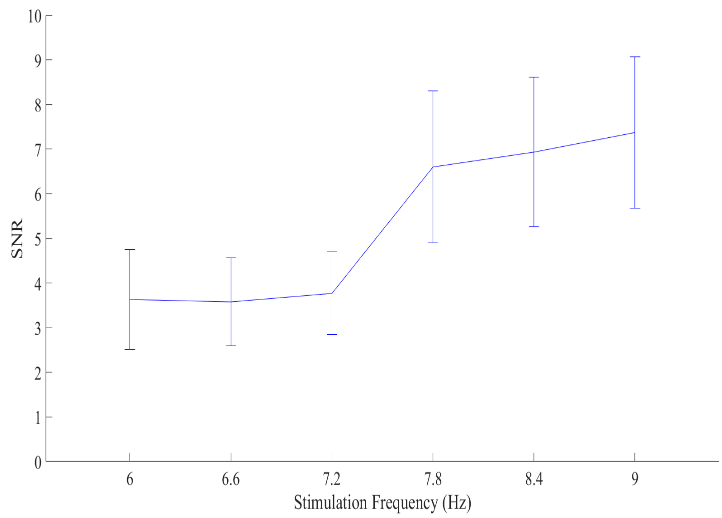
(a) Configuration I (*placement I* and big Stimulus)



(b) Configuration II (*placement I* and small Stimulus)



(c) Configuration III (*placement II* and big Stimulus)



(d) Configuration IV (*placement II* and small Stimulus)

Fig. 4.3 SNRs for different configurations. The values from obtained from all four electrodes have been averaged. The error bars represent standard error of means (SEM).

4.5.3 Accuracy

Accuracy values of all subjects were averaged and plotted in figure 4.4 for all 4 configurations. The information conveyed by the graph is similar to that conveyed through SNR in the previous section. There is a distinct improvement in accuracy for *placement II* when compared to *placement I*. However, there is not much difference in accuracies obtained from configurations III and IV.

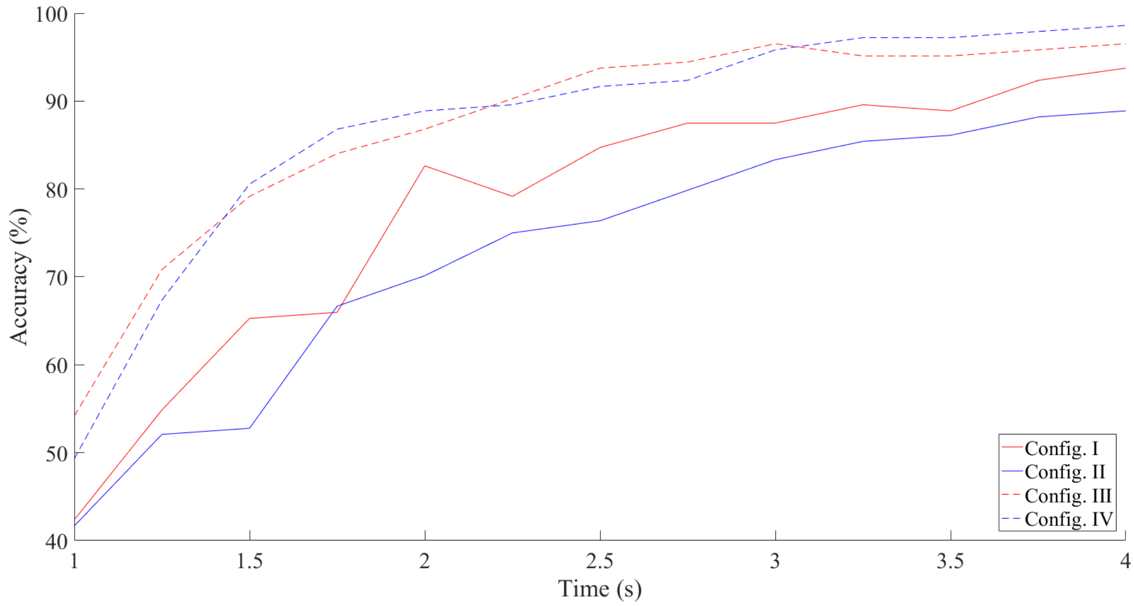


Fig. 4.4 Accuracy vs time graphs for all 4 configurations.

4.6 Discussion on Optimisation

This chapter proposed two parameters for optimisation — headset placement and stimulus size. The first parameter was based on the prediction that the electrodes might not be reaching the occipital region of the subject's head. The second parameter was directed towards increasing inter-stimulus distance, which might improve the classification accuracy of the flashing regions. Section 4.5 denoted that *placement II* is the optimal method to deploy the headset on the subject's head. As there is no clear distinction between the performances of configurations III and IV, let us consider additional factors — (i) One of the objectives of this thesis is to increase the number of user-available choices in BCMIs. This project presented 6 choices. In order to increase the number of choices in future research, configuration III is not suitable because most of the computer screen has been occupied by the flashing regions.

(ii) 5 out of 6 subjects favoured configuration IV because of smaller size of flashing regions. The system caused less visual fatigue and psychologically, there was less interference from neighbouring stimuli.

This thesis reports an interesting observation regarding the relationship between stimulus size and stimulation frequency. In figures 4.3c and 4.3d, SNR for the big stimulus is greater than the small stimulus for the first three stimulation frequencies, but it is lower for the next three stimulation frequencies. This conveys that bigger stimuli are more favourable for lower frequencies and vice versa. This novel observation can be verified with the graph presented in Duszyk et al. (2014) in figure 2. Stimulus size of 170 pixels performed better than 255 pixels for a stimulation of 30Hz, but performed worse for lower frequencies. However, the chapter does not speak about this phenomenon. Therefore, this chapter suggests the use of varying stimulus sizes for SSVEP-based systems in future research. Figure 4.5 plots SNR values for big stimulus, small stimulus, and their mean. In order to draw a linear relationship, SNR has been calculated with respect to magnitude instead of power (that is, the magnitude has not been squared). The mean curve resembles a sigmoidal function, which is a commonly used function in statistics and machine learning. The mean values have been fit into a sigmoidal curve by the using the *sigm_fit*[2] function in MATLAB and depicted in figure 4.6. The stimulus sizes can be calculated by the following equation.

$$S_{\mathrm{k}} = S_{\mathrm{max}} - (S_{\mathrm{max}} - S_{\mathrm{min}})F_{\mathrm{sigm}}(k\Delta f) \tag{4.3}$$

where k is the stimulus number (k = [1,6]), S_{max} is the size of big stimulus (3.02 inches), S_{min} is the size of the small stimulus (1.21 inches), and Δf is the difference between consecutive stimulation frequencies ($\Delta f = 0.6Hz$). The sizes of the flashing regions calculated from equation 4.3 are 2.96, 2.84, 2.52, 1.99, 1.53, and 1.32 inches. However, this particular design of the visual stimulus is a hypothesis and has not been verified with experiments. These experiments are beyond the scope of this thesis and are relevant for future work. This chapter deduces that configuration IV is the optimal one for SSVEP-based BCMIs.

4.7 Proposed BCMI System

4.7.1 Performance

This section compares the performance of BCMI systems presented in the current and previous chapter. Apart the 6 subjects who have tried configuration IV, the system is tested on S3 and S7. For different time windows, information transfer rates (ITRs) of the new system

[2] sigm_fit function : https://uk.mathworks.com/matlabcentral/fileexchange/42641-sigm_fit.

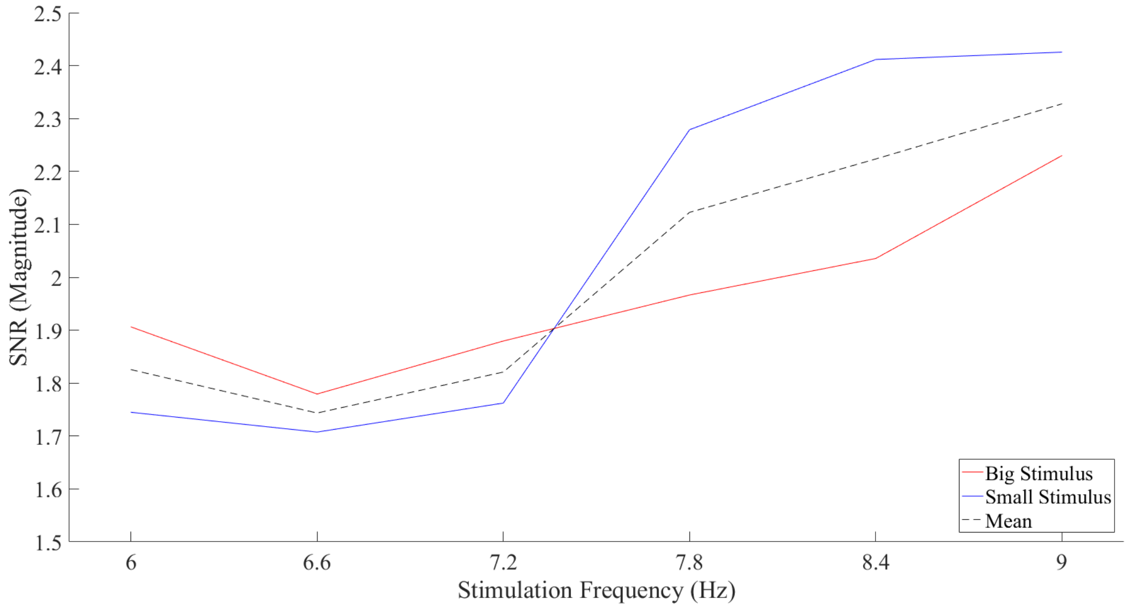


Fig. 4.5 SNR values of the big stimulus, small stimulus, and their mean.

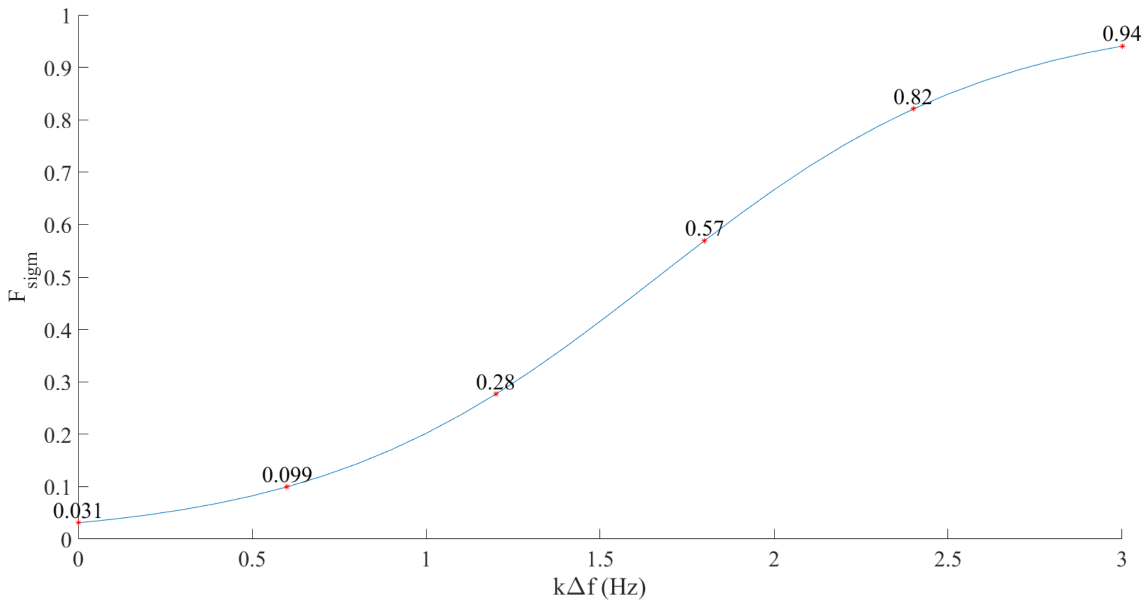


Fig. 4.6 Mean values from figure 4.5 are fit into a sigmoidal curve.

are plotted in figure 4.7. The optimal window is found to be 2s and the corresponding ITR is 35.56 *bits min*$^{-1}$. In comparison to the previous system, this is an increase of 8.78 *bits min*$^{-1}$. Table 4.2 tabulates the accuracies and ITRs of all subjects for 2s and 4s. For a data length of 4s, there has been an increase in accuracy and a reduction in standard deviation (from 8.87 to 2.22). Furthermore, all subjects attained an accuracy of greater than 95%. This demonstrates that the optimisations have made the system more universal and robust. For a time window of 2s, the mean accuracy is 88.02%, but the standard deviation is 9.30%. This denotes that the optimal time window is not common for all subjects.

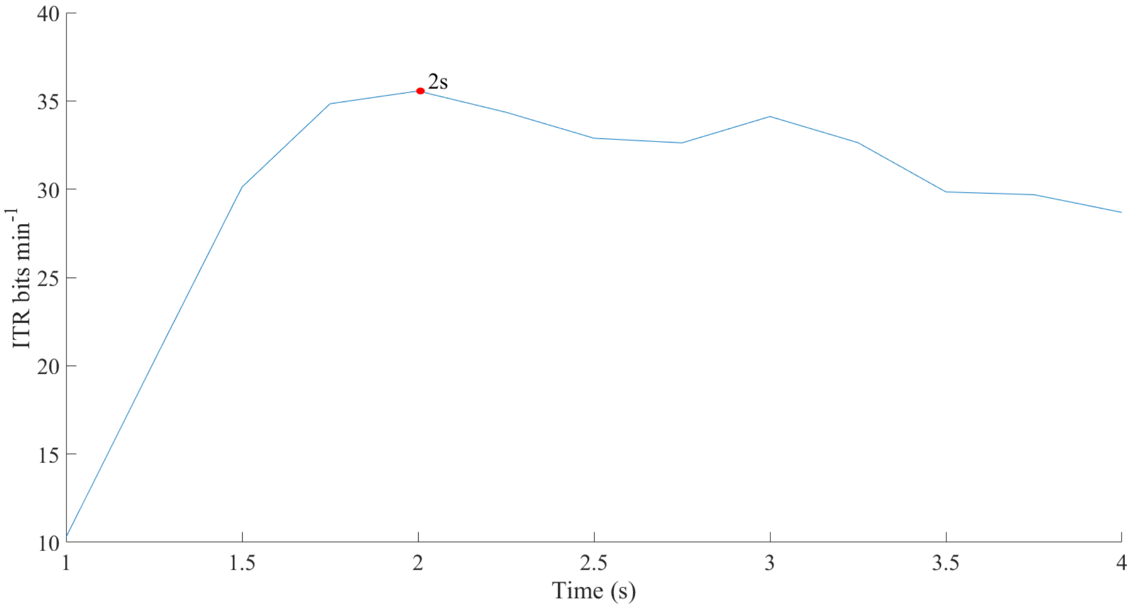


Fig. 4.7 Average ITRs of optimal BCMI for different time windows.

	Accuracy (%)		**ITR (bits min^{-1})**	
Subject	**2s**	**4s**	**2s**	**4s**
S1	83.33	95.83	30.95	26.86
S2	95.83	100.00	44.77	31.02
S3	91.67	95.83	39.55	26.86
S4	95.83	100.00	39.55	26.86
S5	95.83	100.00	44.77	31.02
S7	79.17	95.83	27.26	26.86
S8	70.83	95.83	20.74	26.86
S9	95.83	100.00	44.77	31.02
Mean	88.02 ± 9.30	97.92 ± 2.22	36.56 ± 9.17	28.94 ± 2.22

Table 4.2 Accuracy and ITR values of all 8 subjects for time windows of 2s and 4s.

Considering the above observations, this chapter proposes the use of subject-specific time windows for the BCMI system. Empirically, it was noticed that subjects performed differently on different days. Therefore, the optimal time window might not be constant. This might be due to physiological reasons, subject's mental state, and experimental set-up (minor variations in headset placement and contact between electrode and skin). Hence, it will be effective to run 2 test cases with the subject before using the online BCMI system. The time taken for each test case is 60s (4s of flashing stimuli and 1s of relax time, which appear 12 times). After doing so, the subject can choose an optimal time window for the BCMI.

4.7.2 Stand-alone BCMI

The previous chapter analysed EEG by using MATLAB. This section discusses the implementation of EEG analysis and audio output within the C++ application framework. In the online system, the computer does not instruct the user to gaze at a specific region. Instead, it detects the choice of the user. The user is expected to gaze at flashing regions for the optimal time window (2 , 2.25, 4s, etc.) and the system produces the output during the relax time. For the sake of convenience, let the duration for which the regions flash be called *analysis time*. Alongside audio output, a visual animation indicates the choice made by the user. During the relax time, the user can shift the gaze to another target in order to make the next choice.

4.7.2.1 Analyse EEG

There are 2 important processes to be implemented for EEG analysis — filtering and audio output. MATLAB's *filtfilt* function implements zero-phase filtering by matching initial conditions (MathWorks, 2018). It extrapolates the signal to match starting and ending transients by using algorithms adapted from Gustafsson (1996). This thesis uses MATLAB's code generator[3] to translate the filtering code to C++. However, MATLAB's code generator currently does not support *canoncorr*. CCA involves complex mathematical calculations like inverse square roots and eigendecompositions of matrices. This has been developed with the support of Eigen, which is C++ template library for linear algebra (Eigen, 2018). In order to implement CCA, Härdle and Simar (2003) was referred to for an in-depth explanation on the procedure.

[3]MATLAB's code generator: https://uk.mathworks.com/products/matlab-coder.html

4.7.2.2 Audio Output

JUCE is an application framework that is used by many companies like Cycling '74, KORG, M-Audio, Image Line, Akai, etc. to develop commercial audio software. Thus, it provides robust support for music technology applications. In the literature, BCMIs have generally used MIDI to produce output. These MIDI signals are passed to an external instrument to produce audio. BCMIs have also generated musical scores, which are played by an external musician (Eaton, 2016). As audio processes are computationally expensive, EEG analysis and audio output are carried out by separate processors. This trend was observed in earlier BCMIs developed within the ICCMR lab. The current project aims to encapsulate all BCMI-based operations into one stand-alone application, which would make them more usable for practical deployment in real-world scenarios.

This project aims to output audio files instead of generating MIDI data or musical scores. These sound samples were composed in collaboration with Prof. Eduardo Miranda. Apart from improving portability, the use of samples would provide more flexibility to the system. By this method, the system only requires sound samples of what the user would like to play. As mentioned earlier, it can be used to trigger different musical instruments, soundscapes, timbres, and so on. Waveform Audio File Format (WAVE or commonly known as WAV) is a popular audio file format used for storing audio (Microsoft, 2018). JUCE supports playback for WAV files and all sounds in this project were stored in this format.

4.7.2.3 Icons

This thesis aims to present a stand-alone framework to build a variety of musical applications. In order to improve the interactivity of the musical application, the use of graphical icons have been explored. These icons are royalty-free images obtained from *Flaticon*[4]. If these icons are overlapping with the flashing regions, there might be a decline in the performance of SSVEP. Hence, the icons are visible during the relax time of the system. Considering the computational load of the visual stimulus, EEG analysis, and audio playback, rendering 6 different images through the CPU may lead to performance issues. Therefore, these icons are rendered by using OpenGL textures, which harnesses hardware-accelerated rendering. All the icons are loaded from a single image and the texture coordinates are mapped accordingly. Figure 4.8 is a snapshot of the interface which allows the user to choose from six different categories of sound samples.

[4] Flaticon: https://www.flaticon.com/

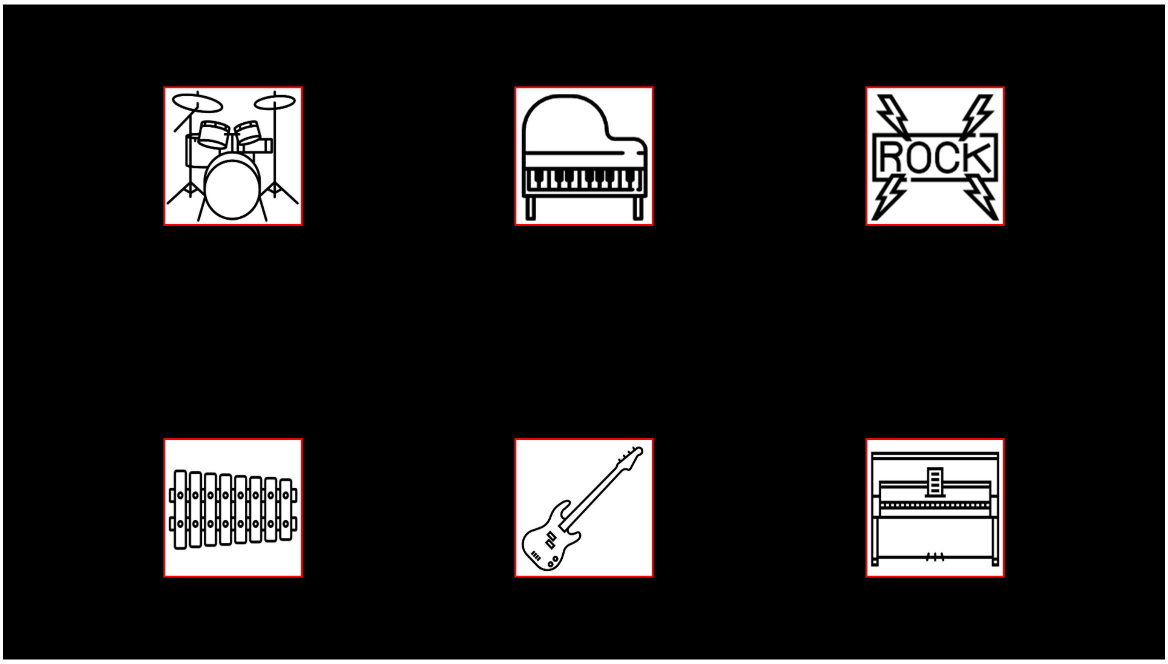


Fig. 4.8 Snapshot of the BCMI during the relax time. It allows the user to choose from 6 different classes of sound samples.

4.7.2.4 Relax Time

In BCI literature, the main function of the relax time is to allow user to shift the gaze from one choice to the other. However, in BCI-based musical systems, there other crucial aspects that are related to relax time. Firstly, this project adopts a bespoke control flow, in which the 6 choices offered to the user is not constant. The choices vary from screen-to-screen (the control flow is explained in detail in the next section). Thus, the relax time needs to be long enough for the user to view all options. Secondly, the duration of the sound sample effects the relax time. The following equation needs to be satisfied by the BCMI.

$$Duration\ of\ sound\ sample \leq Analysis\ time + Relax\ time. \tag{4.4}$$

If the sound sample is shorter than the relax time, the output is played only during the relax time. If the sound sample is longer than the relax time, the previous output is played when the user is making the next choice. This shortens the delay between the consecutive choices made by the user. If the sound sample is greater than the sum of the relax time and analysis time, the previous output would be interrupted by the next output, which is not favourable. However, exploring polyphonic sounds in BCMIs is beyond the scope of this thesis.

4.7.3 Control Flow

This thesis offers the user 6 different choices presented in the screen. The number of applications that can be developed with 6 static and binary choices is limited. Therefore, this chapter explores the development of a multi-screen BCMI. This way, the options presented on the next screen would be based on the choice made by the user in the previous screen. The proposed BCMI system has been divided into two programmes — BCMI set-up and musical system. The former programme is used to find the optimal analysis time and relax time, which is specific to the individual. Figure 4.9 depicts the control flow of the programme. Each step in the control flow presents a separate screen with exclusive choices. The set-up programme has an analysis time of 4s and a relax time of 10s. This would allow the user to enter choices with high accuracy and provide reasonable time to view the different options present on the screen. The first screen allows the user to either run tests to find an optimal window or directly enter it. If the subject chooses to run tests, then in one separate screen the subject's accuracy vs time results are displayed. In the next screen, the user is allowed to choose from six analysis times: 1.5, 2, 2.5, 3, 3.5, and 4s. Intermediate values are omitted limit the number of options to 6. Based on the analysis time and the longest sound sample, the systems finds a minimum relax time $R_{\min}$. The user is offered with 6 different relax times — $R_{\min}$, $R_{\min}+2s$, $R_{\min}+4s$, $R_{\min}+6s$, $R_{\min}+8s$, and $R_{\min}+10s$. If the user has no prior experience with the musical system, a long relax time would be appropriate and vice versa. It is important to note that the screen is blank (with only the border of the regions visible) for 0.3s before the transition from relax time to analysis time. By adding this transition, the user would expect the regions to start flashing instead of an unforeseen onset.

The musical system programme has two screens that provide different set of choices — sound libraries and sound samples. In the first screen, the user can choose between 6 different sound libraries — drum kit, piano, rock, vibraphone, guitar, and ambience. In the second screen, the user can trigger 5 different sound samples from the respective library and the 6$^{\text{th}}$ option is to return to the first screen. Figure 4.10 illustrates the control flow of the musical system.

4.8 Concluding Discussions

This chapter investigated methods to improve the communication rates of BCMIs. There were two parameters analysed for optimisation — placement of headset and size of the visual stimulus. The former predicted that occipital electrodes might not be reaching the occipital region of the subject's head and the latter considered that an increase in visual angle might improve classification accuracy. The different combinations of these two parameters

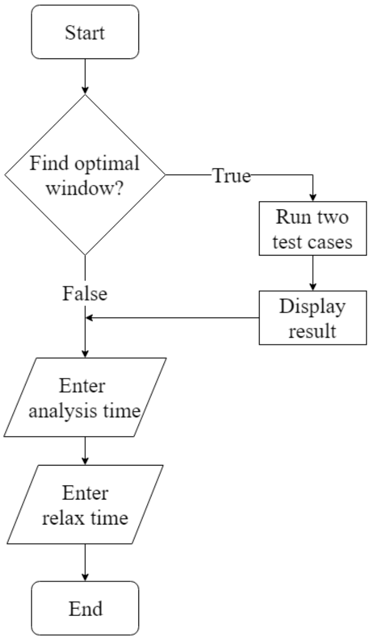


Fig. 4.9 Flowchart of representing the BCMI setup.

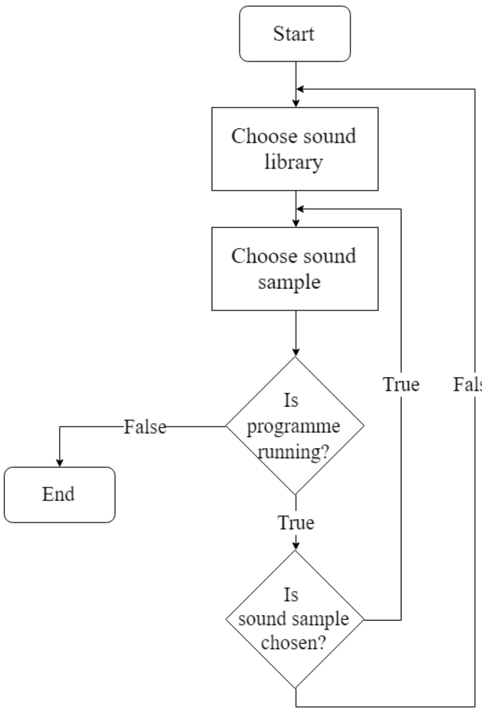


Fig. 4.10 Flow chart representing the musical system.

gave rise to four possibilities of configurations. The chapter deduced that *placement II* is more appropriate for SSVEP-based BCIs. It realised improved SNR and accuracy values. This is due to the phenomenon that *placement II* detects higher SSVEP amplitudes when compared to *placement I*. The size of the stimulus did not reveal a clear-cut result with respect to SNR and accuracy. However, it was deduced that smaller stimulus size allows future expansion in the number of choices and caused less visual fatigue. Therefore, this chapter reckoned configuration IV (that is, *placement II* and small stimulus size) as the most favourable arrangement for the system. The new system surpassed ITRs of previous BCMIs and the system discussed in the previous chapter. These factors contribute to answering RQ2. Moreover, this project adopted wireless and dry EEG headsets. For a data length of 4s and 2s, it realised an accuracy of 97.92% and 88.02%. Apart from an increase in accuracy, there was a considerable reduction in standard deviation, which made the system more universal. It was noted that the optimal time window is not the same for all subjects. Therefore, the chapter stressed on the importance of user-specific time windows. Furthermore, this chapter observed a relationship between the stimulus frequency and size — smaller sizes are more suitable for higher frequencies and vice versa. However, this proposition was not utilised by this thesis and it formed the foundation for future work. SSVEP-based BCIs that incorporate varying stimulus sizes is an interesting possibility to explore. Figure 4.3 illustrated that 7.8, 8.4, and 9.0 Hz had higher SNR than 6, 6.6, and 7.2Hz. This is contrary to the assumption made in section 3.3.1.2, which states — lower frequencies elicit greater SSVEP amplitudes (Chen et al., 2014). Therefore, using a slightly higher frequency range for SSVEP might lead to an improvement in communication rates.

A stand-alone BCI for musical applications was presented in this chapter. It used MATLAB's code generator to translate the filter designed in section 3.4.3 into C++ code. CCA was implemented with the support of *Eigen*, which enabled complex mathematical operations to be easily performed. Audio files were used as the medium of output for the BCMI, which enabled the user to choose from a variety of sound samples. OpenGL textures were adopted to make the interface more interactive. Collectively, these developments have answered RQ1 and improved the usability and portability of BCMIs. This thesis proposed a novel control flow for BCMIs. It considered the limited number of choices offered by the BCMI and hence, explored the use of a multi-screen BCMI, in which one screen leads to the next. There were two sub-programmes developed by this project — BCMI set-up and musical system. The former allowed the user to independently find an optimal time window without the need for an external individual. This would be helpful for patients who are suffering from motor disabilities. The second programme allowed the subject to choose a sound library as well as trigger sound samples.

This chapter concluded that the optimal time window is not common for all subjects. Most BCI research chapters that adopt CCA as the analysis paradigm, use a common time window for all subjects (Bin et al., 2009b; Chen et al., 2014; Nakanishi et al., 2014b). As these experiments use wet EEG detectors, the inter-subject variation might be less noticeable. Therefore, this thesis harnessed time windows that were specific to subjects. Initially, in order to avoid long training sessions for subjects, this project focused solely on unsupervised CCA. However, after obtaining results from experiments, it suggested that tests must be conducted to optimise time windows. Since the user's data is anyway being collected during this phase, it would be advantageous to explore machine learning paradigms. The user's data can be more extensively used to optimise analysis techniques and improve the speed and accuracy of BCMIs.

Chapter 5

Conclusion and Future Work

5.1 Overview

In this project, a stand-alone BCI system was developed for musical applications. It is advantageous for musicians who want to explore a novel dimension of control and beneficial for patients who are suffering from motor disabilities. This chapter summarises the various conclusions that have been drawn from the research process. On one hand, it has made BCMIs more usable for practical deployment in real-world scenarios and on the other hand, it has improved the communication rates of these systems. Apart from the research questions, there were some additional inferences deduced by the project, which have been discussed. This chapter also offers pathways for future work, which can be adopted for research in this interdisciplinary field.

5.2 Reflection on Research Questions

This section discusses about how this project has answered the 2 research questions.

RQ1 *How can we make BCMI technologies more usable for practical deployment in real-world scenarios?*
The second chapter conducted a survey on 4 different BCMI systems — passive, motor imagery, P300, and SSVEP. Among the 2 criteria used for comparing these systems, the first one focused on the usability of the BCMI. Among all systems, passive BCMI was evaluated as the most usable system. However, considering the other criterion of comparison, which focused on the communication between the user and the system, SSVEP was the most suitable approach for this project. The chapter also presented a brief introduction to the

paradigms for SSVEP. It conceived as SSVEP as a promising technique to make BCMIs more usable for practical deployment in real-world scenarios.

Contribution 1.1 — *Using dry and wireless headsets*
All experiments in this project were conducted by using a dry and wireless EEG headset manufactured by Cognionics, Inc. The headset detected EEG signals from 4 different regions of the head — Cz, Pz, O1, and O2. As additional substances like gel are not required for the headset, the set-up time for the experiment was small. Electrode impedances of under $250k\Omega$ was achievable within a time of 10 minutes. The headset was powered by Bluetooth and data was received by a dedicated thread within the BCMI application. The results presented in chapter 3 and 4 proved the reliability of the headset for SSVEP-based BCMIs.

Contribution 1.2 — *LEDs or big monitor screens are not necessary to present the visual stimulus.*
Initially, LEDs were preferred over LCDs because of the limitation imposed by the monitor's refresh rate. For instance, Eaton (2016) adopted LED panels to present the visual stimulus. This project employed sinusoidal stimulation (Manyakov et al., 2013), in which the refresh rate need not be divisible by the stimulation frequency. Moreover, this project was developed and tested on a *17.3 inch* laptop. Generally, BCI systems have used external monitors of sizes 21 to 23.6 inches (Wang et al., 2017, 2012). This restricts portability because monitors are normally bulky. Using a more compact platform such as a laptop would improve the usability of BCMIs. The visual stimulus was realised with the help of OpenGL. *Shader* programmes were developed to allow the GPU to perform hardware-accelerated rendering. VSync was enabled to synchronise the display rate of the LCD and frame rate of the application. Therefore, this thesis demonstrated the robustness of the laptop for SSVEP-based BCMIs.

Contribution 1.3 — *Development of a stand-alone BCMI system.*
The third chapter contributed to RQ1 by investigating methods to develop stand-alone BCMI systems. Out of the 4 operations of BCMIs, 2 were implemented within this chapter — presenting the visual stimulus and receiving EEG. An offline analysis was carried out in MATLAB and an optimal signal processing algorithm was designed. In the fourth chapter, MATLAB's code generator was used to realise the filtering algorithm and the *Eigen* library was incorporated to implement CCA. The project harnessed audio classes supported by JUCE to produce output. All sounds were stored in the format of WAV files. The 4 BCMI-based

operations were encapsulated into one module with the help of multi-threading, which allows them to be executed simultaneously.

Contribution 1.4 — *Development of BCMI with a novel control flow.*
In the fourth chapter of the thesis, a fully usable BCMI system was presented. It considered the fact that only 6 choices are offered to the user at an instance of time. Therefore, the chapter explored the use of a multi-screen BCMI, in which the user's choice in the previous screen influences the options offered in the next screen. Within this thesis, two different online programmes were created — BCMI set-up and musical system. The former allowed the user to independently configure the BCMI without the requirement of an external individual. This is helpful for patients suffering from motor disabilities because they can set the analysis time and relax time by themselves. In the musical system, the user was allowed to choose a musical instrument in the first screen and the play the instrument in the second screen. In order to make the system more interactive, graphical icons were displayed during the relax time. OpenGL textures were used to render the images on the screen by using the GPU.

RQ2 *How can we improve the communication rates of BCMI systems?*
Among passive, motor imagery, P300, and SSVEP systems, SSVEP offers the highest rate at which the user can communicate with the interface. Therefore, this project focused on developing a SSVEP-based BCMI and improving its communication rates. In comparison to earlier BCMI systems, this project attained a notable improvement in communication rates. This is due adopting joint frequency phase modulation (JFPM, Chen et al. (2015b)) as the stimulation technique, analysing harmonic frequency components, filtering EEG data, and employing an optimal headset placement. The following summarises the contributions towards answering RQ2.

Contribution 2.1 — *Analysing harmonic frequencies*
Müller-Putz et al. (2005) observed the presence of harmonic frequencies in SSVEP. Since then, several chapters incorporated harmonic components in their EEG-analysis to improve the performance of BCIs (Bin et al., 2009b; Chen et al., 2014; Lin et al., 2007). However, these experiments used medical-grade EEG headsets to detect brain waves, which offer comparatively high SNR. In order to understand the impact of harmonic frequencies in dry

EEG recordings, this thesis conducted an offline analysis. An improvement in communication rates was observed until 5 harmonics. However, beyond 5, there was no noticeable difference.

Contribution 2.2 — *Filtering improved the performance of the system.*
Chen et al. (2015a) proposed a technique called filter bank canonical correlation analysis (FBCCA) for SSVEP-based BCIs. The chapter explored the use of a filter bank, which is an array of band-pass filters. It was proven that FBCCA improves the communication rates of BCIs. The design of each band-pass filter for this paradigm involves a high-pass and low-pass filter in cascade. In order to obtain a steep roll-off in the low-pass filter, it generally requires a very high filter order. Furthermore, zero-phase filtering is performed. These two factors considerably increase the computational cost. This thesis designed a bespoke filter for the BCMI. It comprised a high-pass and notch filter placed in cascade. The experiments demonstrated that filtering improves the accuracy of BCMI systems. Therefore, there is a possibility for low-pass filters to be eliminated during FBCCA and still achieve the same performance. In future work, for FBCCA, an array of high-pass filters can be incorporated instead of band-pass filters.

Contribution 2.3 — *It is optimal to use subject-specific time windows.*
In chapters 3 and 4, the optimal time windows based on averaged performance of subjects are 2.25s and 2s respectively. In comparison to the third chapter, the fourth chapter realised a distinct improvement in communication rates. Furthermore, there was a decrease in standard deviation, which showed that the system was applicable to a wider range of subjects. However, despite optimising parameters, a common analysis time was not suitable for all subjects. Therefore, section 4.7.2 designed two different online BCMIs, where the first programme allowed the user to configure the analysis time of the system. Contrarily, in BCI experiments that adopt CCA, a common time window is obtained. As this project adopts a dry and wireless EEG headset, the inter-subject variation may be more noticeable.

Contribution 2.4 — *Configuration IV, that is smaller stimulus size and placement II (refer to section 4.3 for more details) is most favourable for SSVEP-based systems.*
In this thesis, four different configurations were tested to optimise parameters for SSVEP-based BCMIs. They are (i) big stimulus and placement I, (ii) small stimulus and placement I, (iii) big stimulus and placement II (iv) small stimulus and placement II. Experiments showed that the placement of the headset evidently influenced the performance of the system. The SNR for placement II was greater than the SNR for placement I. This is due to the fact that placement II recorded EEG signals from regions that comprised higher SSVEP amplitudes.

On the other hand, stimulus size did not show a clear-cut effect on the performance of the system. Few subjects felt that neighbouring flashing regions were interfering while using the system. However, psychological observations need not be in coherence with physiological responses. Moreover, most subjects agreed to the fact that the smaller stimulus caused less visual fatigue and was easier to look at. Hence, the smaller stimulus size was more favourable for SSVEP-based BCMIs.

5.3 Other Concluding Discussions

In addition to answering the research questions, this thesis presented other conclusions that were not directly related to the research questions.

Contribution 3.1 — *Lower stimulation frequencies need not elicit higher SSVEP amplitudes.*
This thesis developed a BCMI system that incorporated a dry EEG headset that detects signals from four electrodes. It was assumed that lower frequencies elicit higher SSVEP amplitudes (Chen et al., 2014). In order to compensate for the comparatively poor SNR of dry EEG, the lowest possible stimulation frequencies were chosen. However, in section 4.4.2 it was found that 7.8, 8.4, and 9.0Hz realised higher SNR than 6.0, 6.6, and 7.2Hz. This concludes that the project has not chosen the optimal set of stimulation frequencies for SSVEP. Therefore, revising the set of frequencies could improve the performance of BCMIs.

Contribution 3.2 — *Greater stimulus sizes are more suitable for lower frequencies and smaller stimulus sizes are more suitable for higher frequencies.*
This was an interesting observation made in section 4.6, which indicated a relationship between stimulus size and stimulation frequency. On one hand, lower frequencies worked better with bigger flashing regions and on the other hand, higher frequencies worked better with smaller flashing regions. Equation 4.3 delineated this relationship with the help of a sigmoidal curve, where the stimulus size could be optimised with respect to the stimulus frequency. SSVEP-based BCIs could be redesigned to adopt a visual stimulus with varying stimulus sizes. However, this is a hypothesis and it needs to be confirmed with tests.

5.4 Future Work

This project combined elements of neuroscience, biomedical engineering, and computer music. Interdisciplinary research at the intersection of these three fields offers bright potential for future research. The following are possible pathways that can be adopted for future research.

Pathway 1 — *Re-designing the headset used to detect EEG*
The quick-20 headset used by this project detects EEG from 4 different regions — Cz, Pz, O1, O2. The highest SSVEP amplitude is generally observed in the occipital and parieto-occipital regions (Chen et al., 2014; Wang et al., 2008). Although Cz and Pz may not realise a significant SSVEP amplitude, they pick up similar noise signals. Thus, they assist in improving SNR. Furthermore, this project incorporated CCA as the analysis paradigm, which implies — greater the number of EEG channels, better the SNR. However, generally in BCI-research, headsets with high electrode-densities in occipital and parieto-occipital regions are used (Bin et al., 2009b; Chen et al., 2015b). Hence, an alternative design such as POz, Oz, O1, and O2 may be more appropriate for SSVEP-based systems. During the experiments, few subjects complained about pressure being exerted from the Cz electrode. Special considerations can be taken to minimise inconveniences caused to the subjects. Furthermore, this project adopted EEG because it is a non-invasive and cost-effective method. Depending on future developments in biomedical engineering, alternative brain-scanning methods like functional magnetic resonance imaging (fMRI, Weiskopf et al. (2004)) and fast optical signals (Proulx et al., 2018) may become more viable options.

Pathway 2 — *Finding an optimal set of frequencies.*
Many researchers have proposed an optimal range of stimulation frequencies for SSVEP. For instance, Nakanishi et al. (2014b) used 8 to 15Hz, Chen et al. (2015b) used 8 to 15.8Hz, and Demir et al. (2016) used 6 to 10Hz. As these research articles use medical-grade and wet EEG sensors, a separate comprehensive study needs to be conducted in order to find an optimal range of stimulation frequencies for dry EEG. In section 4.4.2, the lower 3 frequencies realised lower SNRs than the higher 3 frequencies. Therefore, in future research, a higher set of frequencies can be used to design the visual stimulus.

Pathway 3 — *Optimising signal processing techniques by incorporating phase features.*
This project adopted JFPM as the stimulation technique. Alongside unique frequencies, the flashing regions are encoded with a unique phase. Unique phases make the flashing regions more discriminable. However, in this thesis unsupervised CCA was used, in which there is no training data from the user. Hence, phase features were not considered while analysing EEG.

In future research, phase can be included in the analysis paradigm to improve communication rates of the system.

Pathway 4 — *Explore machine learning to improve communication rates.*
One of the objectives of this thesis is to reduce inter-subject variation in performance. By using user-specific time windows, appropriate stimulus size, and optimal headset placement, the BCMI system was applicable to a wider range of subjects. This thesis developed a BCMI system that does not require training data. However, in order to obtain an optimal time window, user's data needs to be collected. Therefore, this data can be harnessed to improve the performance of the BCMI. Furthermore, researchers have explored machine learning paradigms for BCIs. Manyakov et al. (2013) generated class-feature pairs based on a fuzzy system (Rutkowski, 2008) to study phase characteristics. Nakanishi et al. (2014b) used signal averaging and template-matching to improve the speed and accuracy of SSVEP. Thus, in future research, these machine learning paradigms could be explored for dry EEG. Simultaneously, the number of flashing regions on the screen could be increased to offer the user more number of choices. This would increase communication rates and offer more flexibility while designing the control flow of the BCMI.

Pathway 5 — *Investigating the size of the stimulus with respect to the stimulation frequency.*
This thesis demonstrated a relationship between the size of the stimulus and the stimulation frequency. However, in order to test this hypothesis, it requires a comprehensive set of experiments to be conducted. Currently, it is predicted that the size of the stimulus is governed by a sigmoidal curve. Alternatively, it is possible that a linear or exponential relationship may lead to better performance. Studying this phenomenon may also lead to an increase in the range of stimulation frequencies used for SSVEP.

Pathway 6 — *Exploring alternative stimulation paradigms for BCMIs.*
This project adopted SSVEP as the paradigm for providing the user with active control. One drawback of SSVEP is the continuous exposure of the user to flashing stimuli. Using such a system over a long period of time may not be practical. This reduces the usability of the system for long-term use and musical scenarios. Alternative stimulation techniques such as steady state motion visual evoked potential (SSMVEP) have been proposed by Guo et al. (2008); Yan et al. (2017). In this paradigm, movement of graphical objects elicit frequencies in EEG. As this project has already developed a strong foundation for integrating computer graphics with BCIs, implementing new stimulation techniques would be relatively straightforward. This project harnesses SSVEP for musical applications and perhaps, the

stimulation technique could include musical or audio parameters. For instance, visual and auditory stimulation can be combined to improve interactivity the of the BCMI. Rhythmic nature of music can be explored with respect to the rhythmic nature of EEG.

5.4.1 Suggested Research Questions

The above pathways are condensed into the following research questions.

- What are the design-considerations to develop a dry and portable EEG headset that is appropriate for SSVEP?
- How can we optimise the set of stimulation frequencies that are used for SSVEP in dry EEG?
- How can we creatively incorporate phase features while analysing brain waves by using statistical processing techniques?
- How can machine learning paradigms improve the communication rates of BCMIs?
- Does a visual stimulus that presents varying stimulus sizes offer better speed and accuracy?
- What are the stimulation techniques that are specifically advantageous to BCMIs as opposed to general BCIs?

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Appendix A

Ethical Declaration

The information sheet given to the subjects who participated in the experiments is as follows.

A.1 Information Sheet

Project: Investigation into Stand-alone Brain-computer Interfaces for Musical Applications
Email of researcher: satvik.venkatesh@students.plymouth.ac.uk
Name of supervisor: Prof. Eduardo Miranda
Email of supervisor: eduardo.miranda@plymouth.ac.uk

What is this project about?

This project explores the development of brain-computer interfaces (BCIs) for musical instruments. It aims to develop a piano that can be played solely by gazing at flashing icons on a computer screen. These systems are beneficial for patients who are suffering from motor disabilities. However, please note that at this stage of my project I am not working with patients of any kind. All tests, for which I am seeking this ethical approval are to be conducted with my colleagues and students in the ICCMR lab — who have normal or corrected-to-normal vision.

The system presents a computer screen with multiple icons flashing at different frequencies. It enables the user to make choices from the screen by gazing at individual icons. It uses a wireless headset manufactured by Cognionics, Inc. to detect electroencephalogram (EEG) signals. This headset is worn by the subject while performing tests. The objective behind performing these tests on different subjects is to ascertain how quickly and accurately users can select icons displayed on the screen.

What will you have to do if you agree to take part?

The experiment comprises a computer monitor screen with multiple flashing icons. The subject is required to gaze at a specific region that is indicated by a visual cue within the screen. Brain waves are detected with the help of an electroencephalogram (EEG) headset manufactured by Cognionics, Inc. The headset is to be worn by the subject during participation. EEG data will be recorded from 10 individuals and anonymously stored. The experiment is accompanied by an optional questionnaire that would ask for their gender and age. Again, this would be anonymously collected from the subjects.

Day 1

The screen contains different icons that are emitting white light. There will be 13 or fewer icons on the screen. Subjects will be asked to gaze at each icon for 6 seconds no more than 6 times. Subjects will be informed of which icon to gaze at by a visual cue that appears on the screen.

Each subject will be asked to avoid blinking while performing tests. Rest of few minutes will be given at regular intervals (after 1 or 2 cycles of tests). The expected duration for each subject to gaze at the monitor for the entire experiment is less than 8 minutes. The data collected from day 1 will be used to improve the system's speed for tests on day 2.

Day 2

Day 2 tests are split into two parts. Firstly, similar tests as day 1 will be conducted. However, subjects will be asked to gaze at each icon for 2 seconds 17 times. Once again, there will be rests of 10 seconds every time the system has cycled through each icon once.

The second part consists of users playing a melody by gazing at flashing icons that are arranged on the screen to mimic a keyboard. This test will take approximately 2 minutes. The expected duration to gaze at the monitor is less than 10 minutes.

Informed consent

The subject's participation is voluntary and the recorded data would be kept anonymous.

Openness and honesty

All methods and experimental procedures have been explained in detail and there is no undisclosed information.

Right to withdraw

The subject can withdraw during the experiment and 3 days after completion. The data would be anonymised after 3 days. His or he consent will be taken before analysing the data. The subject can choose to delete his or her data until this time.

Protection from harm

Experimental procedures used in the project are safe, non-invasive, and widely incorporated in the field of brain-computer interfaces. Performing these tests over a prolonged period of time can cause visual fatigue. Experiments in other laboratories last approximately 15 minutes. However, the tests conducted within this project span less than 10 minutes to avoid minimise the chance of visual fatigue.

What are the advantages or disadvantages of taking part?

The subject's participation will be contribution to the field of brain-computer interfaces (BCI). He or she will have the opportunity to play a musical instrument through unconventional means.

The subject will have to perform experiments without blinking. Performing these tests over a prolonged period of time can cause visual fatigue. Hence, rest for several minutes will be given between blocks of tests.

Debriefing

These tests are conducted to estimate speed and accuracy of the brain-computer music interface system developed in the project. The subject may obtain information on my progress and request copies of outputs at any time by contacting the researcher through the above contact details.

Confidentiality

The recorded data would be kept anonymous. Generalised information like number of subjects and age-range of all subjects would be revealed. Statistics like speed and accuracy would be anonymously stated.

Planned outputs

The results of the study will be documented in the Research Masters thesis of Satvik Venkatesh. These tests were conducted to estimate the accuracy and speed of the system. All future publications for conferences and journals based on these tests would present statistical information like speed and accuracy. It would also include generalised information for example, *"10 subjects (6 males and 4 females) participated in these experiments."* Any other information would not be presented. All participants are invitied to contact Satvik Venkatesh after the tests for updated information on resulting outputs.

Feedback

Please feel free to contact Satvik Venkatesh at any time if you have questions regarding this research study.